Doctoral Thesis

Understanding and characterizing past, present, and future hydroclimatological change

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Understanding and characterizing past, present, and future hydroclimatological change

A thesis submitted to attain the degree of

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presented by

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Abstract

Changes in the hydroclimatological conditions of the land surface induce widespread impacts on a variety of socio-economic sectors. Assessing past and projected hydroclimatological changes is therefore essential. Nonetheless, the substantial complexity of the hydroclimatological system and the associated data and methodological uncertainties do often not permit conclusive assessments. Also, the wealth of metrics and definitions regularly create conflicting results. In order to foster a clear communication of changes in dryness/wetness to policymakers and the public, observed and anticipated changes are occasionally summarized into simple catchphrases, like e.g. the ‘dry gets drier, wet gets wetter’ paradigm. However, such summaries carry the risk of oversimplifying the governing relationships.

This thesis consists of two parts both separated into two chapters. The first part of this thesis aims at identifying regions of robust past and projected trends in dryness/wetness using observations-based data for the 2nd half of the 20th century and model data for the 21st century, respectively. Dryness and wetness changes are assessed through the joint analysis of water availability (precipitation - evaporation, \( P - E \)) and aridity (ratio of potential evaporation and precipitation). The statistical approach used allows to determine the geographical distribution of significant hydroclimatological trends.

Regarding the assessment of past changes (Chapter 2), the large amount of existing datasets and possible dataset combinations is evaluated using the Budyko framework as a reference model. By doing so, the selection of physically consistent dataset combinations is enabled and reliability is added to the trend assessment. The trend analysis then reveals that for ca. 3/4 of the global land surface no robust trends are detectable. For the remaining 1/4, significant wetting is identified in parts of North and South America, and drying is found in many parts of Africa, East Asia and the Mediterranean. Using the aridity index to classify regions as either humid or arid allows the evaluation of the ‘dry gets drier, wet gets wetter’ paradigm. It is found that for less than half of the area with robust trends the paradigm is confirmed. Thus, the paradigm is in total supported for ca. only 11% of all land area.

Regarding future changes (Chapter 3), it is first shown that the widely-used \( P - E \) (water availability) metric alone is not adequate to assess land
drying/wettening. Trends in water availability are identified as significant only in some northern high latitude regions over land. Additionally considering aridity reveals more regions experiencing significant drying, especially located in the Mediterranean and adjacent regions. However, jointly considering both metrics, still ca. 70% of the land surface show no robust trends. Validating the ‘dry gets drier, wet gets wetter’ paradigm using both metrics reveals that the paradigm is not supported for ca. 1/3 and supported for ca. 2/3 of the remaining land area. Overall the paradigm is accordingly confirmed for only ca. 20% of all land area, mainly for regions in southern Europe and the northern high latitudes. It does not explicitly apply to the remaining 80% and a few cases of expanding drylands into adjacent regions are identified that specifically invalidate the paradigm. In summary, we conclude that the ‘dry gets drier, wet gets wetter’ paradigm does not serve as a valid summary of observed and projected hydroclimatological changes over global land areas.

The second part of the thesis is dedicated to the Budyko framework. The Budyko framework is a well-established, semi-empirical and simple hydrological model to relate mean annual aridity and water availability. Due to its simplicity it is widely recognized as a powerful hydrological tool and is used to validate and to test datasets on physical consistency in Chapter 2 of the present thesis. However, it is still subject to certain limitations. Two of these limitations are addressed in the second part of the thesis: (i) the nonlinearity of the underlying Budyko space in combination with the deterministic nature of the Budyko curve (Chapter 4) and (ii) the limitation to steady-state conditions (Chapter 5).

By using a formulation of the Budyko curve that includes a free parameter, the first issue is addressed by developing a probabilistic representation of the framework. For this new representation, the free parameter ω, which represents the combined influence of landscape and climatic characteristics of a catchment is assumed to follow a probability distribution. This step allows the formulation of a probabilistic Budyko model. The distribution of the parameter is further estimated from a set of catchments in the United States, suggesting that the parameter follows a gamma distribution.

In a second assessment, the same formulation is used to derive a Budyko framework implicitly accounting for the case of nonstationary water balance conditions and to enable its use on other than mean annual catchment scales. The new formulation is derived by relaxing the boundary condition that represents the supply limit. By doing so, an additional parameter, which is physically well defined, is obtained. The remaining first parameter is indeed very similar to the single parameter of the stationary Budyko curve. The new framework is evaluated against a standard set of datasets. By doing so, a reasonably good performance at monthly time scales is shown.

In conclusion, this thesis shows that both past and future changes in
hydroclimatological conditions over land are subject to major uncertainties, which do not permit an identification of robust trends for the majority of global land areas. Further, the widely-used ‘dry gets drier, wet gets wetter’ paradigm is determined to not represent observed and anticipated changes. The second part of this thesis further highlights that addressing major limitations of the Budyko framework is potentially of greater importance in order to enhance the fundamental knowledge and range of potential applications, than the yet not conclusive assessments aiming to identify potential physical controls determining the basic characteristics of the Budyko framework. In this context, two expansions of the Budyko framework are introduced: (i) a probabilistic, rather than deterministic, and (ii) a nonstationary, rather than stationary framework.
Zusammenfassung


Durch die Verwendung einer Formulierung des Budyko-Modells, welche eine freien Parameter beinhaltet und aus einfachen Grundannahmen analytisch hergeleitet wird, ist es möglich ein probabilistisches Budyko-Konzept


Im zweiten Teil wird argumentiert, dass die grundsätzliche Untersuchung von Limitierungen des Budyko-Konzepts wichtiger sein könnte die zukünftige Nutzung des Konzepts voranzubringen als die bisher nicht abschliessende Zuordnung von möglichen physikalischen Kontrollprozessen. In diesem Zusammenhang wird eine probabilistisches, im Gegensatz zum traditionell deterministischen und ein nicht-stationäres, im Gegensatz zu einem stationären Konzept eingeführt.
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Introduction

Climate change is regarded as a key challenge facing human society in the 21st century. Modern industries, transportation systems, power and food production, as well as political and social developments are all highly vulnerable to changes in the climate system. Further, climate-induced ecosystem shifts will potentially have substantial effects on vegetation distribution, food webs, animal extinctions, as well as global distributions of parasites and diseases. Climate impacts on socio-economic and ecosystem-related sectors are often related to changes in the global water and energy cycles (Allen et al., 2014).

The cycling of water and energy on Earth is governed by a complex interplay between all components of the climate system: the oceans, cryosphere, atmosphere, and land surface, including vegetation and soils. The focus of this thesis lies on the detection of changes in physical processes describing the exchange of water and energy between the land surface and the atmosphere at mean annual time scales. Potential shifts towards a drying or wettening in the hydroclimatological conditions of the land surface are a consequence of all interactions between the respective processes. The identification and correct interpretation of such interactions is subject to a variety of assessments. Although simplifications are commonly used to explain and communicate past, present, and future changes in the water cycle, it is important to assess their validity in the view of the underlying uncertainties.

Hydroclimatological changes are mainly assessed through the analysis of observations or observations-based datasets, whereas future changes are
solely assessed through climate or Earth System Models (ESMs) of differing complexity. The latter constitutes the main basis for the climate assessment reports prepared by the Intergovernmental Panel on Climate Change (IPCC). ESMs represent the current knowledge of the climate system and numerically integrate the most important underlying physics and interactions between a vast amount of different processes. A great advantage of such complex models is their comprehensiveness but their use for numerical experiments and projections requires substantial computer power and time. Thus, simpler approaches and models enjoy great popularity for more specific purposes and conceptual analyses. Among these approaches, the Budyko framework experiences a revival in recent years.

This introduction chapter first introduces in Sec. 1.1 the basics on the water cycle and the coupled land water and energy balances. The wealth of various data sources and methods available to assess hydroclimatological changes is outlined in Sec. 1.2. An overview of the current knowledge on changes in the hydroclimatological conditions of the land surface is then provided in Sec. 1.3. The Budyko framework, which is central for the present thesis is introduced and discussed in Sec. 1.4. Finally, the aims of the thesis are presented in Sec. 1.5.

1.1 Background

In the following section, I provide a short overview on the basic physical characteristics underlying the water cycle (Sec. 1.1.1) and the coupled land water and energy balance (Sec. 1.1.2).

1.1.1 The water cycle

The components and underlying physics of the water cycle are outlined in the following by mainly focusing on processes related to the exchange of water between the atmosphere and the land surface. However, exchanges between the land surface and the oceans as well as processes related to the interactions between the atmosphere and the oceans/cryosphere are also introduced.

Illustrated in Fig. 1.1, the amount of water stored in any form (liquid, gaseous or solid phase) in each reservoir varies strongly. By far the largest fraction of Earth’s water is stored in the oceans ($1,355,040,10^3$ km$^3$). Among the other reservoirs, ice ($26,350,10^3$ km$^3$, i.e. water stored as either sea ice or glaciers) and groundwater reservoirs ($15,300,10^3$ km$^3$) store as much as a hundred-times more water than rivers and lakes ($178,10^3$ km$^3$) and soil moisture ($122,10^3$ km$^3$). Even smaller amounts are stored in the atmosphere ($12.710^3$ km$^3$) and in permafrost soils ($2210^3$ km$^3$). Given the small amount of water permanently stored in the atmosphere, the residence time of a water molecule in the air is lowest, being about a few days to one week in high latitudes, and ca. 2-3 weeks in subtropical regions (Trenberth, 1998).
1.1. BACKGROUND

Figure 1.1: The water cycle. Estimates of the main water reservoirs, given in plain font in $10^3 \text{ km}^3$, and the flow of moisture through the system, given in slant font ($10^3 \text{ km}^3 \text{ yr}^{-1}$). From Trenberth et al. (2007)

Water cycling on the Earth follows the principle of mass conservation. The large amount of water being evaporated over the oceans is thus either contributing to precipitation occurring over the oceans themselves (90%) or transported to land surfaces, where it contributes to land precipitation (10%). Precipitation over land consists of ca. 35% water originating from the ocean surfaces. The residual 65% originate from water being evaporated from inland water surfaces, from the soil, through transpiration of plants and intercepted water at the canopy. Since the flow of water from and to the oceans should balance, the relative percentage of land precipitation running off into the oceans, either via surface or subsurface flow is 35% as well. The residual land precipitation is contributed to reservoirs over land, being rivers/lakes, soil moisture, groundwater storage, and permafrost/glaciers. The water being stored in the rootzone of the soils is again available to plants and partly transpired back into the atmosphere.

Although the total mass of water is retained, the individual reservoir storages and the relative amount of water being exchanged between the reservoirs are subject to a variety of processes in the climate system and likely to modifications with climate change. From a socio-economic perspective, the amount of water stored in the soil, as groundwater, in permafrost soils and in rivers/lakes is of major interest (IPCC 2007, 2014: Meehl et al., 2007; Stocker et al., 2014).
1.1.2 The coupled land water and energy balance

The land water and energy balance equations represent the principles of mass and energy conservation. Illustrated in Fig. 1.2 and expressed as,

\[
\frac{dS}{dt} = P - E - R_s - R_g, \tag{1.1}
\]

the land water balance for a given terrestrial system including a surface soil layer and vegetation, establishes that the amount of water entering the system via precipitation \((P)\), is balanced by changes in water storage of the soil layer \((dS/dt)\) and water leaving the system (evapotranspiration \(E\) and surface \(R_s\) or subsurface \(R_g\) runoff). It is important to note that any additional water input by lateral transport of water from adjacent systems is not considered in this approach. Furthermore, the term \(E\) includes different processes of water leaving the respective system. These include evaporation from either the bare soil, from surface water or from water intercepted and stored at the canopy, transpiration, and/or snow/ice sublimation. Furthermore, the storage term includes, besides water stored in the soil, also water being stored as surface water, snow or ice.

The land water balance (1.1) is coupled to the energy balance equation through \(E\):

\[
\frac{dH}{dt} = R_{net} - \lambda E - SH - G. \tag{1.2}
\]

The evaporation of water (or the sublimation of snow/ice) is associated with an exchange of energy, being expressed as \(\lambda E\) (i.e. the latent heat flux), with \(\lambda\) being the latent heat of vaporization (sublimation). Similarly to Eq. 1.1, the amount of energy entering the system via net radiation \(R_{net}\) is balanced by either a change in heat stored within the system \(dH/dt\), the transfer of heat directly to the atmosphere (that implies a temperature change) through sensible heat flux \(SH\), or the transfer of heat through a mediating matter, that is mainly associated with a phase change of water (and thus implies no temperature change) and defined as latent heat flux \(LH\) (or \(\lambda E\)). A transfer of heat within the soil to layers outside the respective system is defined as the ground heat flux \(G\).

The amount of energy entering the system via net radiation \(R_{net}\) is the sum of incoming and outgoing radiation components, both in the longwave/infrared radiation and the shortwave (mainly visible) radiation spectrum.

It is obvious from Eqs. 1.1 and 1.2 that any change in the water balance components, which consequently results in a change of the water cycle, is interrelated to changes in the energy balance component. Evapotranspiration \(E\) is not only constrained by the amount of water available in the respective terrestrial system (soil moisture), but also by the amount of available energy. Thus, \(E\) could be either energy-limited, in regions with more water available...
1.2. DATA SOURCES AND METHODS

The complexity of processes governing changes in hydroclimatological conditions do not permit a comprehensive assessment of trends towards drier or wetter conditions. Past studies use a large variety of methods covering either single or combinations of climate variables and involve many different data sources. This heterogeneity potentially implies a very large uncertainty to be evaporated than the actual amount of energy available to evaporate surface water or water limited, in regions with large amounts of available energy but lower availability of water. The underlying concept is depicted in Fig. 1.3 and based on the work of Budyko (1948, 1974) (see Sec. 1.4 for more details). In a wet soil moisture regime with values below the wilting point $\theta_{\text{wilt}}$, no evapotranspiration is possible. In a transitional regime, above $\theta_{\text{wilt}}$ and below a certain critical soil moisture value $\theta_{\text{crit}}$, a change in evaporative fraction $EF$ is proportional to a change in soil moisture. For wet soil moisture conditions, $EF$ is solely constrained by the available energy.

Considering this framework and the interactions between Eqs. 1.1 and 1.2, it is central in the present thesis to consider both changes in the water balance components, as well as the energy balance components concurrently to assess hydroclimatological changes.

1.2 Data sources and methods

The complexity of processes governing changes in hydroclimatological conditions do not permit a comprehensive assessment of trends towards drier or wetter conditions. Past studies use a large variety of methods covering either single or combinations of climate variables and involve many different data sources. This heterogeneity potentially implies a very large uncertainty
and increases the need for simplifying summaries of observed and anticipated changes.

In the present thesis, a large number of datasets originating from different sources is used. These datasets cover the variables of the hydroclimatological system and associated climate parameters related e.g. to vegetation. Thereby, the used datasets are subdivided into observations-based and model-based estimates.

**Observations-based data estimates**

Meteorological and hydrological variables are measured hourly, six-hourly or daily at a large number of stations (unevenly) distributed across all continents. The total number of featured stations varies between particular collections depending on different quality control and homogenization approaches, but usually includes several thousand stations covering time periods since the 1950s and several hundred stations with time series of up to 100 or more years. (e.g. Peterson and Vose, 1997; Jones and Moberg, 2003; Donat et al., 2013). However, station density is naturally very large in highly populated areas of the world, like e.g. Europe, North America and China, but considerably low in remote regions, like e.g. deserts or tropical rain forests. Most of these stations provide measurements of temperature and precipitation, a large amount of stations also provides measurements of sea level pressure, relative humidity and wind. A certain amount of stations and additional measurement sites also provide estimates of radiative components. For example, the Global Energy Balance Archive (GEBA) entails a total of more than 2000 stations providing measurements of radiation and other energy flux components (Wild et al., 2012, 2014).
1.2. DATA SOURCES AND METHODS

Water, energy and carbon flux estimates retrieved via eddy-covariance measurements at large towers, mainly located in Europe and North America, are organized within the FLUXNET-initiative (Baldocchi et al., 2001). These measurements are valuable due to their comprehensiveness, but are however subject to large uncertainties regarding energy balance closure (Wilson et al., 2002; Foken, 2008). Further, the lack of flux tower observations in tropical to subtropical regions, as well as polar regions represents a major downside.

Station measurements covering hydrological variables such as streamflow are often measured with gauging devices at rivers and river mouths. The Global Runoff Data Base (GRDB) provided by the Global Runoff Data Centre (GRDC) lists a total of ca. 9000 gauging stations worldwide, providing streamflow measurements from small to largest catchments (Retrieved 3 March 2015 from their website at http://www.bafg.de/GRDC/EN/01_GRDC/13_dtbose/database_node.html). Similarly to other observational networks, river gauging networks are very dense in Europe, North America and Australia, but however, a lack of measurements is found in most tropical and polar regions.

Regarding temporal availability, first measurements of climate variables at a point scale date back more than 150 years. Since ca. 1980, another source of observations using satellites is available. Remote sensing of the atmosphere, the land surface and the oceans revolutionized climate observations and provided further insights on all aspects of the climate system. A wealth of techniques and algorithms is used to retrieve climate information from sensors mounted on satellites in geostationary, low or Sun-synchronous orbits. Measurements of clouds and their properties, aerosols, skin temperatures (land and ocean), soil moisture, ocean salinity, vegetation properties, etc. over large regions present advantages compared to point scale measurements regarding their spatial coverage, but are also subject to large uncertainties.

Station measurements (sometimes in combination with satellite measurements) are further used to generate gridded data products. These products interpolate (or extrapolate) point scale measurements to a predefined regional or global grid. Gridded products allow for a better spatial comparison with satellite observations and model estimates and are thus often used in climate assessments, as well as in the present thesis. Nonetheless, the step from point-scale measurements to a final gridded product involves many assumptions regarding the gridding technique, station weighting, quality control, etc., each adding uncertainty to the final dataset. Besides standard interpolation techniques (bilinear, conservative, etc.) modern machine learning tools are also employed to derive gridded data estimates (Jung et al., 2010; Gudmundsson and Seneviratne, 2015).

Thus, given the variety of underlying techniques to generate gridded data, assessments including several observations-based datasets of different climate
variables can be problematic in case of lack of prior checking regarding the consistency of particular data products’ combinations. In the present thesis a method to check the consistency between different precipitation, evapotranspiration and potential evapotranspiration products based on the Budyko framework is developed (see Chapter 2).

**Model-based data estimates**

Another source of data products used in the present thesis originates from climate or, in particular, land surface models. Generally speaking, climate models numerically solve the physical equations governing the dynamics and interactions between the different components of the climate system discretized on a grid. Modern climate models (generally termed Earth System Models, i.e. ESMs) incorporate the knowledge of the most important physical, chemical and biological processes shaping the Earth’s climate. The land surface and its role within the climate system is represented through land surface models (LSMs), which explicitly solve the equations governing the transfer of water and energy within, into and out of the soil, including the transfer of water, energy and momentum induced by vegetation. LSMs could be used interactively within the climate models, thus specifying the interactions between the atmosphere and the land surface, or in offline mode using atmospheric forcing only, without including feedbacks to the atmosphere.

Climate models (and LSMs, respectively) could be either used to hindcast past climate or to project future conditions. Hindcasting past climate via models by incorporating observations allows to reanalyse past conditions on a global scale. These reanalysis products are a valuable source to assess past changes in the climate system, also because many climate parameters are estimated simultaneously within a consistent model framework. Nonetheless, different approaches to incorporate observations (and observational errors) via data assimilation add uncertainty to reanalysis data products.

Future projections with climate models follow certain assumptions about the future development of greenhouse gases, so called Representative Concentration Pathways (RCPs). Four RCPs build the foundation to force climate models until 2100 within the Coupled Model Intercomparison Project Phase 5 (CMIP5) related to the Fifth Assessment Report (AR5) of the IPCC (IPCC 2014: Stocker et al., 2014). The different RCPs consider different models of future development of society, thus providing either optimistic estimates, with greenhouse gas emissions starting to decline in the first half of the 21st century (RCP2.6 and RCP4.5), or rather pessimistic estimates, with greenhouse gas emissions rising until the end of the 21st century (RCP6) or even beyond 2100 (RCP8.5). Following these forcing scenarios, projections are usually conducted until 2100. These predict an increase in temperature, sea level rise, and substantial regional impacts on precipitation and water availability (IPCC 2007, 2014: Meehl et al., 2007; Stocker et al., 2014). Further details
on future projections regarding hydroclimatological variables are provided in Sec. 1.3.2. However, many factors add uncertainty to these projections. These are e.g. uncertainties due to internal variability preventing the detection of robust signals, structural uncertainties of the climate models, and uncertainties related to the forcing scenarios.

**Data uncertainty**

Taking the aforementioned variety of data sources into account, the data choice itself constitutes a major source of uncertainty in all assessments analysing climate change. Studying hydroclimatological change further requires a joint analysis of various variables and thus the inclusion of combinations of datasets. Arbitrary combinations are, however, not necessarily physically consistent. In Chapters 2 and 3 of the present thesis, a comprehensive number of datasets and model simulations is used. To address both the data uncertainty and consistency among dataset combinations, new methods are introduced to allow for a robust assessment of past and future hydroclimatological changes.

Nonetheless, uncertainty also arises from different methodologies used to assess change in the hydroclimatological components of the Earth system. A short overview on various methods to analyse drying/wettening is provided in the next subsection.

**Methodological uncertainty**

The different components of the water cycle are related through various processes in a rather complex system, basically not permitting to conclusively identify changes in land-related dryness/wetness. Depending on a certain focus (e.g. agriculture, power production, transportation, etc.), particular components are usually rated to be of major importance, others to be of minor importance.

Studying a single component of the water cycle could provide interesting, though inconclusive knowledge on changes in the hydroclimatological system. Most prominently, changes in precipitation are studied to assess changes in dryness (also referred to as meteorological drought) and wettening (e.g. Zhai et al., 2005; Zhang et al., 2007; Min et al., 2008; Zhou et al., 2008; Allan et al., 2010; Hoerling et al., 2009; Chou et al., 2013). Changes in runoff (hydrological drought) constrain water availability and do have potential influence on water resources management (e.g. Groisman et al., 2004; Dai et al., 2009; Piao et al., 2010; Stahl et al., 2010, 2012; Lorenzo-Lacruz et al., 2012). For a variety of purposes it is also of interest to study changes in evapotranspiration (Jung et al., 2010; Wang et al., 2010; Mueller et al., 2011; Douville et al., 2013; Mueller et al., 2013). Another important component of the water cycle is soil moisture impacting agriculture, whereas changes in soil moisture
are usually assessed by studying deviations from the mean state (soil moisture anomalies, SMA) (Wang, 2005; Seneviratne et al., 2012; Orlowsky and Seneviratne, 2013). Another factor used to study dryness/wetness change is relative humidity, representing the relative water vapor content of the near surface air, which is itself related to temperature (Dai, 2006; Willett et al., 2008; Berry and Kent, 2011; Willett et al., 2010, 2013).

Although changes in single components could be of interest for a particular purpose, they are by no means representing the big picture of hydroclimatological change. Analysing combined changes of various variables using different methods potentially provides more comprehensive insights. Among these, the difference between precipitation and evaporation ($P - E$) is often used to assess changes in water availability (from a land hydrological viewpoint) or atmospheric dynamics (interpreting $P - E$ as atmospheric moisture convergence) (Held and Soden, 2006; Dai, 2013; Liu and Allan, 2013).

Another metric being of importance from a land hydrological perspective is the ratio of precipitation over potential evaporation, usually referred to as aridity index (Budyko, 1974). Potential evaporation is the amount of evaporation that would occur if the available water were not constrained, thus representing the energy limit on evapotranspiration. Potential evaporation depends on various factors including net radiation, vapor pressure deficit, wind speed, vegetation, etc. Having an aridity index much smaller than one indicates wet (energy-limited) climate regimes where precipitation exceeds the amount of potential evaporation. An aridity index much larger than one instead refers to dry (energy-limited) climate regimes. Changes in aridity index are assessed in many studies (Zhang et al., 2009; Feng and Fu, 2013; Fu and Feng, 2014; Sherwood and Fu, 2014; Roderick et al., 2014) and the aridity index is further substantial to the Budyko framework used in the present thesis and introduced in Sec. 1.4.

Instead of using average values of precipitation, the Standardized Precipitation Index (SPI) is based on the normalized distribution of the deviations from the mean value (McKee et al., 1993). Thus high or low SPI denotes either very wet or dry conditions and is usually used to identify dryness and wetness and whether these significantly change (Lloyd-Hughes and Saunders, 2002; Hirschi et al., 2011; Mueller and Seneviratne, 2012; Seneviratne et al., 2012; Orlowsky and Seneviratne, 2013). However, being based on a single variable, SPI features some major downsides. In recent years, the so-called Standardized Precipitation Evapotranspiration Index (Vicente-Serrano et al., 2009, SPEI) is used in many assessments in order to represent the interplay of atmospheric water supply and demand (Vicente-Serrano et al., 2013; Beguería et al., 2014; Yu et al., 2014; Cook et al., 2014). The SPEI is based on the difference between precipitation and potential evapotranspiration. However, an issue is the particular approach used to compute potential evapotranspiration (which would e.g. be overestimated for temperature-only based
1.3. Changes in the Global Water Cycle

A metric also widely used for operational drought monitoring is the Palmer Drought Severity Index (PDSI, Palmer, 1965). The PDSI is based on a simple water balance model and was used in various studies to assess past and future changes in dryness (Dai et al., 2004; Cook et al., 2004; Dai, 2011, 2013). However, recent publications identified some limitations in the design of the traditionally applied PDSI approach. One issue was again the representation of potential evapotranspiration with simple temperature-only parametrizations (e.g. Sheffield et al., 2012; Cook et al., 2014). Another identified issue is the influence of discrepancies in precipitation forcing for derived trends (Trenberth et al., 2014), which however, also applies to other offline modeling approaches.

This brief outline of various (and by no means all) methods reveals the difficulty of performing comprehensive assessments to analyse past and future dryness/wetness changes. Especially the use of metrics based on single variables is prone to produce misleading results, since other factors potentially superimpose a signal found for a single variable.

In the next subsections a short overview of past and future assessments studying changes in the water cycle is provided.

1.3 Changes in the global water cycle

In the following, I provide a short overview of studies analysing past changes (Sec. 1.3.1) and future changes (Sec. 1.3.2) in the global water cycle. Furthermore the ‘dry gets drier, wet gets wetter’ paradigm is introduced in Sec. 1.3.3.

1.3.1 Past changes

To summarize past changes regarding single variables such as precipitation, evapotranspiration, runoff, soil moisture and relative humidity I basically refer to results presented in the IPCC AR5 (IPCC, 2014).

Regional trends in mean annual precipitation using three different data products (see Appendix A for more information) and within two time periods (1901-2010 and 1951-2010) are summarized in Fig. 1.4. Data availability is smaller for the longer period and consequently more areas are missing. However, a few hotspots of significant changes in precipitation are consistently found in all three products. These are located in eastern North America and northern Patagonia, experiencing an increase in precipitation in both periods. Almost all products additionally show increasing precipitation amounts in northern Europe. Tendencies towards decreasing precipitation is found for the Mediterranean, especially regarding the more recent time period. Similar tendencies could be identified for parts of eastern Asia and Australia. Nonetheless, Fig. 1.4 nicely shows the uncertainties arising from both data availability and data choice, since identified trends markedly differ locally.
Figure 1.4: Trends in annual precipitation over land from the CRU, GHCN and GPCC data sets for 1901–2010 (left-hand panels) and 1951–2010 (right-hand panels). Trends have been calculated only for those grid boxes with greater than 70% complete records and more than 20% data availability in first and last decile of the period. White areas indicate incomplete or missing data. Black plus signs (+) indicate grid boxes where trends are significant (i.e., a trend of zero lies outside the 90% confidence interval). From IPCC, 2014.
1.3. CHANGES IN THE GLOBAL WATER CYCLE

Regarding river discharge, a general increase in runoff is considered to take place in the northern high latitudes, whereas globally and for large river basins no consistent trend is found. This is mainly due to contradicting results (Groisman et al., 2004; Dai et al., 2009) potentially caused by differing approaches to include assumptions on human influences regarding river management. However, in more regional assessments, partly using small and near-natural catchments, increases (decreases) in runoff have been found to be related to increases (decreases) in precipitation (Groisman et al., 2004; Piao et al., 2010; Stahl et al., 2010, 2012).

Evapotranspiration was generally found to increase globally since the 1980s (Jung et al., 2010; Wang et al., 2010; Mueller et al., 2013), whereas both Jung et al. (2010) and Mueller et al. (2013) identified a decline in global evapotranspiration after 1998, possibly attributable to decreasing soil moisture in parts of South America, southern Africa and Australia constraining evapotranspiration or due to multi-year variations in ENSO (Miralles et al., 2014). Douville et al. (2013) was further showing that past changes in evapotranspiration are attributable to effects of anthropogenic radiative forcing.

Regarding surface humidity, a general increase is found since the 1970s, with a few notable exceptions in various arid land regions (Dai, 2006; Willett et al., 2008; Berry and Kent, 2011; Willett et al., 2010, 2013). However, since the year 2000 relative humidity barely changes at global scales and it further shows some significant decreases in many land regions.

Regarding changes in aridity (which are not explicitly summarized in IPCC AR5) many studies identified an overall increase in aridity within the last 60 years, especially in tropical and midlatitude regions where drylands expand into adjacent regions (Feng and Fu, 2013). Sherwood and Fu (2014) and Fu and Feng (2014) argued that those increases in aridity are directly related to temperature changes and thus a thermodynamic process.

Conflicting results are produced regarding PDSI. A general strong increase in global drought within the 20th century was identified in various studies (Dai, 2011, 2013), but this feature is potentially overestimated since the original formulation of the index (Palmer, 1965) uses a rather simple method solely based on temperature to estimate potential evaporation. By modifying the calculation of the PDSI through using a more sophisticated estimator of potential evaporation both Sheffield et al. (2012) and Cook et al. (2014) found that PDSI trends in the 20th century are actually smaller.

1.3.2 Future changes

Future projections of changes (comparing the 1980-1999 and 2080-2099 time periods) in six different hydroclimatological variables and metrics are illustrated in Fig. 1.5. The displayed changes are the ensemble average of a certain number of CMIP5 models under the RCP8.5 emission scenario.
CHAPTER 1. INTRODUCTION

Figure 1.5: Annual mean changes in \( P \), \( E \), relative humidity, \( E - P \), runoff and soil moisture for 2081-2100 relative to 1986-2005 under the Representative Concentration Pathway RCP8.5. The number of CMIP5 models to calculate the multi-model mean is indicated in the upper right corner of each panel. Hatching indicates regions where the multi-model mean change is less than one standard deviation of internal variability. Stippling indicates regions where the multi-model mean change is greater than two standard deviations of internal variability and where 90\% of models agree on the sign of change. From Stocker et al. (IPCC Technical Summary 2013: 2013)
1.3. CHANGES IN THE GLOBAL WATER CYCLE

For mean annual precipitation, significant increases in future precipitation are found in high latitude land and ocean regions and tropical ocean areas (except over the tropical Atlantic Ocean). A significant decrease of precipitation is mainly found over subtropical ocean areas. It is important to note that over most tropical to midlatitude land areas no significant change in precipitation is detected. Evaporation is generally, with a few notable exceptions, increasing. These increases are however not significant everywhere. Significant trends are located over most ocean areas, excluding some midlatitude ocean regions showing a decrease in evaporation. Over land, a significant increase in mean annual evaporation is mainly located in the northern high latitudes, whereas almost no significant trends are found in subtropical and tropical areas.

Regarding $E - P$ (and overland runoff, respectively) a significant increase over ocean areas is located in all subtropical ocean basins, whereas strong decreases are found in the inner tropics, and smaller, but significant increases in midlatitude to highlatitude ocean regions. The results are generally not significant over land, with the exception of decreasing $E - P$ (and thus increasing runoff) in the northernmost high latitudes, and increasing $E - P$ (and thus decreasing runoff) in most parts of the Mediterranean region and its adjacent areas. Similar signals are also located in parts of southern Africa and South America and Mexico/southern United States. Nonetheless, the vast majority of land area does not show significant trends, in fact many regions are subject to high uncertainty and no agreement between models.

Soils becoming drier are, however, found in many regions, mainly located within the subtropics. Especially in the Mediterranean and north of the Mediterranean, in southwestern North America, south of Amazonia and in southern Africa the identified drying is significant. Nonetheless, large regions, particularly in Asia and Africa show nonsignificant trends (Seneviratne et al., 2012; Orlowsky and Seneviratne, 2013).

Relative humidity interestingly shows a clear land-ocean contrast, with generally wettening air over ocean areas and drying air over land. Decreasing relative humidity is also found over polar oceans. These trends are, however, not significant in many regions, like e.g. in high latitude areas and large parts of Asia and Australia.

In summary, Fig. 1.5 reveals some hotspots of potential future changes in the water cycle over land. These are most notably high latitude regions of Asia and North America, showing a wettening regarding changes in 3 (4) components of the water cycle, being precipitation, evaporation, $E - P$ (and runoff, respectively). Another hotspot is located in the Mediterranean area and its adjacent regions, showing a significant drying also regarding precipitation and $E - P$ (runoff) and additionally soil moisture and relative humidity. Trends in evaporation are, however, not significant. The differing combinations of components involved in the drying of the Mediterranean and the
wetting of the high latitudes reveals that different mechanisms potentially cause such signals. Due to this feature, it is clearly evident that a single metric alone is not appropriate to identify local changes in hydroclimatological conditions. It is also evident that particularly changes in evaporation and soil moisture potentially relate to changes in the energy components.

Not covered in Fig. 1.5 are changes in other metrics like e.g. aridity index or PDSI, which are assessed in various other studies (Seager and Vecchi, 2010; Dai, 2011, 2013; Feng and Fu, 2013; Fu and Feng, 2014; Cook et al., 2014; Sherwood and Fu, 2014; Alessandri et al., 2014). However, we argue that many of these studies are subject to uncertainties related to the parametrization of potential evapotranspiration (as also pointed out in Sec. 1.2). Many approaches to estimate potential evapotranspiration are assumed to be less robust under conditions of projected climatic change reaching beyond present-day conditions under which most parametrization methods have been developed (Milly, 1992; Shaw and Riha, 2011; Milly and Dunne, 2011). Regarding assessments based on climate model data it is also important to note that potential evapotranspiration is not among the standard output of CMIP5. Therefore, in the present thesis, the energy constraint on evapotranspiration in a future climate is estimated by using modeled net radiation (see Chapter 3).

Regarding changes in $P - E$, results of Held and Soden (2006) are often used to summarize the complexity underlying changes in the water cycle in the simple, yet debatable ‘dry gets drier, wet gets wetter’ (DDWW) paradigm. The validation of the paradigm for both past and future changes is the subject of chapters 2 and 3 of the present thesis. In the following section, I shortly introduce the basic principles leading to the widely held assumption that present-day regions will dry out further, whereas wet regions will wetten, and I provide a brief literature review on observations and studies supporting (or not) the DDWW.

1.3.3 The ‘dry gets drier, wet gets wetter’ paradigm

In Fig. 1.6, projected latitudinal changes in $P - E$ derived from an ensemble of CMIP3 (the predecessor of CMIP5) model simulation are shown. Their results indicate an overall increase in $P - E$ in the inner tropics and the midlatitudes and a decrease in subtropical regions. Interpreting $P - E$ as a dynamical component of the atmosphere representing moisture convergence, the global water cycle will intensify leading to an even stronger water loss (divergence) within the dry subtropics ($P - E$ is already negative and gets even more negative), and thus convergence in both the tropics and midlatitudes, which are already humid (positive $P - E$) under present-day conditions. From a viewpoint where $P - E$ serves as a measure of water availability, the results are, however, not that straightforward. This is mainly due to two reasons: (i) The classification of humid/arid areas via $P - E$ is not appropriate over land
1.3. CHANGES IN THE GLOBAL WATER CYCLE

Figure 1.6: The zonal mean $\delta(P - E)$ from the ensemble mean of CMIP3 models (solid) and the thermodynamic component (dashed) predicted from the approach developed in Held and Soden (2006). Results are shown from simulations showing the SRES A1B forcing scenario. From Held and Soden (2006)

since by definition all land areas are characterized by positive $P - E$, and (ii) changes in the energy balance are of major importance in many regions and are not implicitly taken into account in this framework (since changes in the atmospheric water demand are not considered). These issues were also noted by Held and Soden (2006), but nonetheless, latitudinal averages are usually regarded to take place over both land and ocean (see also Fig. 1.7).

A majority of studies conducted in recent years identified hydroclimatological changes consistent with the DDWW paradigm for both past and future changes. Chou et al. (2007) found an increase in the seasonal range of precipitation between wet and dry seasons, which is consistent among models and supports the assumption of an intensification of the water cycle. Allan et al. (2010) found an increase of monthly precipitation regarding the wettest percentages of grid boxes in the tropics using observations within the 1979-2008 period, whereas a decrease was identified in the driest regions. They further determined increasing frequencies of heavy rain in the wettest parts. Using a similar metric, Liu and Allan (2013) attributed a significant DDWW in the 21st century to strong surface warming. In a more regional assessment, Seager and Vecchi (2010) were not able to identify a robust signal in observations that the anticipated drying in the western United States, which should be related to a general drying of the subtropics, is already taking place and a significant signal is not expected before the year 2050. However, also based on long-term observations (1940-2009), Sun et al. (2012) were able to find a general increase in precipitation in dry subtropical regions on the expense of decreases in the wetter inner tropics. Using observations of sea surface salinity over global ocean areas, Durack et al. (2012) found positive trends in
salinity for most subtropical ocean areas, whereas tropical and midlatitude ocean areas show a general decrease in salinity. This indicates a reduced freshwater flux and/or enhanced evaporation (and thus decreasing $P - E$) in subtropical ocean basins and consequently an increase in $P - E$ for other than subtropical ocean areas. Based on observations, Chou et al. (2013) found dry seasons to become more intense in arid areas and vice versa, wet seasons getting wetter in humid regions, thus indicating that the DDWW potentially acts on a seasonal rather than a mean annual time scale. Expanding drylands have further been identified by Feng and Fu (2013) for both observed and projected changes, especially in southwestern North America, Australia, southern Africa and southern to central Europe. Using SPEI, results obtained by Cook et al. (2014) support the findings of Feng and Fu (2013). Alessandri et al. (2014) defined characteristics of the Mediterranean climate type and were able to show that corresponding climatic conditions tend to expand into adjacent regions in Europe and North America. However, small regions of Mediterranean climate type in Southern Africa and Australia were found to be projected to retreat.

These contradictory results are taken into account to carefully evaluate the DDWW paradigm within the present thesis. However, since Chapter 2 uses a rather large number of datasets resulting in a large number of possible dataset combinations regarding water availability and aridity index, these dataset combinations have to be tested on consistency. The Budyko framework is used for this purpose and is introduced in the next section.
1.4 The Budyko framework

In this section\(^1\), I briefly introduce the Budyko framework used as a validation tool in Chapter 2 and which is further subject of new proposed developments in Chapters 4 and 5. Here, I first outline the origins of the framework and define the basic wording which will be used throughout the thesis (Sec. 1.4.1 and 1.4.2). In the following a brief literature review on the variety of formulations and potential physical controls shaping the framework is provided (Sec. 1.4.3) in order to motivate the proposed enhancements presented in the second part of this thesis.

1.4.1 A simple water balance framework

From the beginning of the 20th century, several studies have developed empirical formulas aiming to determine annual streamflow \((Q)\) as a function of prevailing climatic conditions. Schreiber (1904) wanted to calculate mean annual \(Q\) of 30 catchments in central Europe based on precipitation \((P)\) measurements. He used a general and widely used exponential equation, which he assumed was appropriate to describe the relationship between precipitation and runoff:

\[
P - Q = P \left(1 - e^{-\frac{k}{P}}\right),
\]

where he describes \(k\) as a value that is calibrated for each individual catchment. He further argued that \(k\) is the particular value to which \(P - Q\) converges if \(P\) is increased. In hindsight this explanation is conceptually very equal to the concept of potential evaporation. However, Schreiber seemed unaware of the concept of balancing land water components and evaporation itself, raising the question of where the residual of precipitation and streamflow ends up.\(^2\)

Ol’Dekop (1911) modified Schreiber’s equation by identifying that \(k\) could be replaced by potential evaporation \(E_p\) (mm) and adapted the equation of Schreiber (1904) to have an improved empirical fit for his own set of catchments:

\[
P - Q = P \left(1 - e^{-\frac{k}{E_p}}\right),
\]

\(^1\)All parts of this section are written by me and will be part of a review paper on the Budyko framework, which is currently in preparation and to which I contribute as second lead author. In this context, Sec. 1.4.1 includes minor revisions from Wouter Berghuijs. Fig. 1.8 was conceptualized by Wouter Berghuijs and me and produced by Wouter Berghuijs. The other sections (Sec. 1.4.2 and Sec. 1.4.3), however, do not include revisions by others.

\(^2\)Original German text: "Sollte also diese Grundform \[Gleichung 1.3, Anmerkung des Verfassers\] richtig sein, so würde man sich fragen, wohin denn eigentlich das viele rückständige – also nicht zum Abfluss im Flussbett gelangende – Wasser kommt.\" (Translation into English: "If this form \[Eq. 1.3, author’s note\] is correct, the question has to be where the residual water - which is not going into river runoff - remains.\")
CHAPTER 1. INTRODUCTION

Figure 1.8: The Budyko framework, showing the Budyko Curve (red) and the demand and supply limits (dashed lines). The shading denotes the common climate classification based on the aridity index.

\[ E = E_p \tanh \left( \frac{P}{E_p} \right) \] (1.4)

Budyko (1948) suggested that the geometric mean of equation 1.3 and 1.4 agrees slightly better with his empirical data, and accordingly proposed the following relationship:

\[ \frac{E}{P} = \sqrt{E_p / P} \tanh \left( \frac{P}{E_p} \right) \left( 1 - \exp - \frac{E_p}{P} \right) \] (1.5)

It should be noted that Budyko was the first to assess the concept of supply and demand limits, and provided further insights on the physical foundation of the conceptual framework.

The complete framework is illustrated in Fig. 1.8, which provides an overview of the basic definitions used in context of the Budyko framework. The aridity index \((E_p / P, \phi, \text{also referred to as dryness index})\) within the Budyko framework is usually defined as the ratio of potential evaporation \((E_p)\) to precipitation \((P)\) and was already introduced in Sec. 1.2. The aridity index theoretically varies from zero to infinity.

The evaporative index \((E / P, \text{also referred to as evaporation index})\) indicates how much of the incoming precipitation is evaporated, and is usually defined as the ratio between the actual evaporation \((E)\) and precipitation \((P)\).

The Budyko space is the 2-dimensional coordinate system presenting the aridity index on the x-axis, and the evaporative index on the y-axis, in which
1.4. THE BUDYKO FRAMEWORK

mean annual measurements of catchments can be presented, and the Budyko curve can be displayed.

The Budyko curve is the analytical formulation of the mean curve best describing the distribution of sets of mean annual catchment observations within the Budyko space and is defined after Budyko (Budyko, 1948, 1974). It expresses the evaporative index functional on the aridity index.

The Budyko curve is subject to two physical limitations within the Budyko space. The demand limit accounts for the energy constraint on evapotranspiration represented by potential evapotranspiration. The supply limit accounts for the amount of water available for evapotranspiration, which is under steady-state conditions given by water supplied through precipitation. Based on the aridity index, catchments can be classified, as Humid ($\phi < 1.5$), Dry sub-humid ($1.5 < \phi < 2$), Semi-Arid ($2 < \phi < 5$), Arid ($5 < \phi < 30$), and Hyper Arid ($\phi > 30$) (Middleton et al., 1997).

The Budyko framework itself is the combined Budyko space, including the Budyko curve and the energy and water limits.

1.4.2 Long history and recent revival

Assessing the controls shaping the framework was subject to a vast amount of studies since Budyko established the framework in 1948. In this subsection an overview of current knowledge and ongoing research evaluating and extending the understanding of the framework is provided. First, alternative parametric and non-parametric formulations of the Budyko curve are introduced, which are either empirically derived or based on basic theoretical assumptions (Sec. 1.4.2). In a next step, consideration is given to various catchment-specific factors controlling and shaping the framework, including vegetation, soil, seasonality, storminess, topography and other controls. Also assessments evaluating the co-evolution and interdependence of various controls simultaneously are introduced (Sec. 1.4.3). Afterwards, conclusions from the literature review are made to motivate chapters 4 and 5. (Sec. 1.4.3)

Alternative parameterisations

In parallel to the assessments of Budyko, various related relationship have been derived independently in other parts of the world. Here I introduce these approaches in the context of the Budyko framework and the summarize the different formulations in Table 1.1.

Empirical approaches Many alternative parametrizations are based on empirical evidence and result in a numerically similar relationship. Budyko himself used two assessments introduced by Schreiber (1904) and Ol’Dekop (1911) to provide a mathematical formulation of the Budyko curve to represent the relationship between measurements derived from more than 1000
Russian catchments. Using observational data from African catchments, Turc (1955) derived a mathematically different, but numerically very similar formulation of the relationship, which was modified by Pike (1964) on the basis of measurements of large catchments in Malawi. By generalizing the formulation of Pike (1964), Choudhury (1999) introduced another formulation including an adjustable parameter. Independently, based on observations taken in the former German Democratic Republic, Kortüm (1961) modified Schreiber (1904) by introducing an additional parameter summarizing the evaporational processes within the catchment area. However, Kortüm (1961) published his results in German and received no international attention. Later, Zhang et al. (2001) developed an empirical formula including a parameter related to plant-specific water usage. In a more recent assessment, Donohue et al. (2012) combined Choudhury (1999) and a relationship between estimates of plant-available water holding capacity, mean storm depth ($\alpha$) and effective rooting depth introduced by Porporato et al. (2004) to formulate the Budyko-Choudhury-Porporato (BCP) model. By combining different hydrologic models (among them the Budyko model), Wang and Tang (2014) derived a one-parameter relationship independent of temporal scales.

**Theoretical approaches** Apart from the empirical assessments, theoretical approaches considering the underlying basic physical principles and limitations lead to similar formulations of the Budyko curve. A first step was taken by Bagrov (1953) by formulating a differential equation representing the joint evolution of $P$, $E$ and $E_p$, which could also be transferred to Schreiber (1904) equations. Using the approach of Bagrov (1953), Mezentsev (1955) derived an equation identical to that of Choudhury (1999). However, his work was published in Russian and received only little attention. The semi-empirical formula of Pike (1964) and Choudhury (1999) was finally derived analytically by Yang et al. (2008). Another work published in Chinese by Fu (1981) received no attention as well, until it was refered to in the English-speaking literature by Zhang et al. (2004). In his work, Fu (1981) analytically derived an equation based on simple phenomenological assumptions including an integration constant physically representing all catchment characteristics other than the prevailing climatic conditions.

An overview of the mentioned analytical formulations of the Budyko-based models is provided in Table 1.1.

### 1.4.3 Controls on the framework

As discussed above, the Budyko framework establishes the relationship between the aridity index ($E_p/P$) and the evaporative index characterizing the partitioning of precipitation into evapotranspiration and runoff ($E/P$). In
Table 1.1: Overview of Budyko curve equations

<table>
<thead>
<tr>
<th>Reference</th>
<th>Equation: ( \frac{E}{P} = )</th>
<th>Background/Assumptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schreiber (1904)</td>
<td>( 1 - \exp(-\phi) )</td>
<td>Schreiber (1904) suggested the equation without explicit knowledge of the underlying physical principles</td>
</tr>
<tr>
<td>Ol’Dekop (1911)</td>
<td>( \phi \tanh(1/\phi) )</td>
<td>Ol’Dekop (1911) suggested this equation and revisited Schreiber (1904)</td>
</tr>
<tr>
<td>Turc (1955)</td>
<td>( \frac{1}{\sqrt{0.9+(1/\phi)^2}} )</td>
<td>empirical approach based on Schreiber (1904), ( w ) resembles the evaporational activities in the respective area</td>
</tr>
<tr>
<td>Kortüm (1961)</td>
<td>( 1 - \exp(-w\phi) )</td>
<td>modification of Turc (1955)</td>
</tr>
<tr>
<td>Pike (1964)</td>
<td>( (\phi \tanh(1/\phi)(1-\exp(-\phi)))^{\frac{1}{2}} )</td>
<td>geometrical mean of Schreiber (1904) and Ol’Dekop (1911) ( \omega ) is dimensionless free parameter without any a priori physical meaning, equation was derived by Fu (1981) and revisited by Zhang et al. (2004)</td>
</tr>
<tr>
<td>Budyko (1948, 1974)</td>
<td>( 1 + \phi - (1 + \phi^\omega)^{1/\omega} )</td>
<td>( n ) is a dimensionless free parameter without any a priori physical meaning, Mezentsev (1955) provided an ad hoc solution of the derivative ( dE/dP = 1 - (E/E_P)^n ), obtained by Bagrov (1953), Yang et al. (2008) provided the corresponding analytical solution, independently from Mezentsev (1955), Choudhury (1999) suggested this formula by generalizing Pike (1964)</td>
</tr>
<tr>
<td>Fu (1981) and Zhang et al. (2004)</td>
<td>( \frac{1}{(1+(1/\phi)^n)^{1/n}} )</td>
<td>( w ) is the plant available water coefficient, empirical approach</td>
</tr>
<tr>
<td>Mezentsev (1955), Choudhury (1999) and Yang et al. (2008)</td>
<td>( \frac{1+w\phi}{(1+w\phi+\phi^{-1})} )</td>
<td>( \gamma ) contains the average rainfall depth and the soil water holding capacity, equation based on a stochastic model</td>
</tr>
<tr>
<td>Zhang et al. (2001)</td>
<td>( 1 - \frac{\phi\gamma^{\gamma/\phi-1} \exp(-\gamma)}{\Gamma(\gamma/\phi)-\Gamma(\gamma/\phi, \gamma)} )</td>
<td>Budyko-Choudhury-Porporato (BCP) model incorporating estimates of plant-available water holding capacity (( \kappa )), mean storm depth (( \alpha )) and effective rooting depth (( Z_e )) parameter ( \epsilon ) is the ratio of the ratio of the initial evaporation ratio to the Horton index</td>
</tr>
<tr>
<td>Porporato et al. (2004)</td>
<td>( \frac{1}{(1+(1/\phi)^n)^{1/n}} ), with ( n = \frac{0.21\kappa Z_e}{\alpha} + 0.6 )</td>
<td></td>
</tr>
<tr>
<td>Donohue et al. (2012)</td>
<td>( \frac{1+\phi}{(1+(1/\phi)^n)^{1/n}} ), with ( n = \frac{0.21\kappa Z_e}{\alpha} + 0.6 )</td>
<td></td>
</tr>
<tr>
<td>Wang and Tang (2014)</td>
<td>( \frac{1+\phi\sqrt{(1+\phi)^2-4\epsilon(2\epsilon-\phi)}}{2\epsilon(2\epsilon-\phi)} )</td>
<td></td>
</tr>
</tbody>
</table>
this context, the aridity index serves as a surrogate of the prevailing climatic conditions and determines the primary control on the evaporative index. Every process other than the aridity index is referred to as secondary control and potentially alters deviations from the original Budyko curve. Especially in recent years, the influence of secondary controls is assessed in numerous studies. However, due to the vast amount of processes and variables coming into play, none of these assessments is conclusive. Here I provide an overview of the current knowledge and ongoing research related to controls commonly considered to have systematic and strong impacts.

**Single controls**

The following subsection focuses on the influence of single variables and catchment characteristics. Most studies relate deviations from the average Budyko curve to vegetative properties. However, many other potential controls including soil characteristics, seasonality, storminess, and various other controls were also assessed and are summarized in the following

**Vegetation control** Vegetation essentially controls $E$ in every aspect. Transpiration is directly influenced by vegetative characteristics, such as e.g. plant functional type (PFT), root depth, vegetation fraction, leaf area index (LAI) and water use efficiency, establishing a link to carbon assimilation processes. Further, canopy cover and LAI directly influence the amount of intercepted water and shield the underground, impacting bare soil evaporation. Canopy cover and land use index (LUI) also alter the surface roughness and the albedo. The influence of vegetation is thus considered to be of major importance in controlling the partitioning of precipitation into evapotranspiration and runoff.

However, these numerous aspects and vegetative properties alter the actual evapotranspiration value through a wealth of different processes, complicating a conclusive assessment on the control within the Budyko framework. As a consequence, many studies try to identify the importance of single or combined vegetation parameters controlling deviations from the original Budyko curve. Here I provide a comprehensive overview of those studies partly or fully assessing mechanisms of vegetation controls on the Budyko curve.

Budyko himself did not comment on any physical reasoning including vegetation properties on causing deviations from the curve. A few decades later, Milly (1994) investigated potential physical controls determining the partitioning of $P$ into $E$ and $Q$ within the Budyko framework using a stochastical model. In his explanation, this partitioning is determined by seven dimensionless parameters, from which the most important is the aridity index. Among others (see paragraphs on seasonality and hybrids of controls)
the plant available water holding capacity (in relation to $P$) has been determined as an important factor, being itself dependent on root zone depth and root density. Milly (1994) pointed out that large storage values when compared to $P$, tend to dampen $Q$ and promote $E$. However, that study did not examine the actual effect of varying root zone depth or root density as these values were kept constant in his approach. Despite this limitation, an important finding of Milly (1994) was that systematic deviations from the curve are related to out-of-phase seasonality effects of $P$ and $E_P$. Milly and Dunne (1994) suggested a possible explanation for this effect. They hypothesized that in regions with large phase differences in $P$ and $E_P$, vegetation potentially adapted to the conditions and is capable to access water from greater depths under drought conditions. This assumption is supported by Gentine et al. (2012), showing within an inverted Budyko framework that plants adapt to both the aridity index and the peak difference in $P$ and $E_P$ to cope with water stress in dry periods.

Zhang et al. (2001) developed a framework explicitly accounting for several vegetative characteristics being of major importance for the control on $E$. They hypothesized a formulation including a free parameter reflecting the role of those parameters, especially rootzone depth. Calibrating the curve against observations of small to medium-sized catchments further revealed higher $E$ values for forested catchments compared to grassland catchments, a result also supported by Zhang et al. (2004).

Both Milly (1994) and Zhang et al. (2001) identified root zone depth to be important. Based on their assessments, Porporato et al. (2004) introduced a model incorporating dynamic rooting depth and rainfall characteristics. Their results support the findings of Zhang et al. (2001) by showing that the Budyko curve is shifted upwards with increasing rooting depth. Porporato et al. (2004) further used their model to evaluate impacts of changing storm depth on ecological processes.

Evaluating previous assessments, Donohue et al. (2007) argued that incorporating vegetation dynamics into Budyko’s model is essential for its application at small spatiotemporal scales, by showing that variable vegetative properties (namely leaf area index, photosynthetic capacity, and rooting depth) affect steady-state conditions. They further hypothesized that the remotely sensed fraction of Photosynthetically Active Radiation absorbed by vegetation (fPAR) could serve as a useful alternative to represent vegetation dynamics. Using monthly fPAR estimates for Australia, Donohue et al. (2010) tested their hypothesis that incorporating dynamic vegetation into the Budyko framework potentially increases its performance. They found that at mean-annual and large (continental) scales, vegetation-related characteristics are of minor importance to explain the scatter, but are of major importance at medium to small scales.

Yang et al. (2009) found positive correlations between the evaporative
index and vegetation coverage, implying higher E in regions with dense vegetation. This relationship, however does not hold in extremely wet or dry regions where the prevailing climatic conditions are the main controls on the mean annual water balance. Yang et al. (2009) further stated that vegetation coverage itself is mainly determined by aridity index rather than landscape characteristics.

By introducing additional parameters representing land cover information of six broad classes (i.e., cropland, heathland, forest, grassland, shrubland and non-vegetated) into several formulations of the Budyko curve, Oudin et al. (2008) found a small, but significant increase in efficiency within a set of 1508 catchments in the US, France, United Kingdom and Sweden. In contrast to previous findings (e.g. Zhang et al., 2001), a distinct representation of forest properties was found to be of least importance for the computation of the mean annual water balance. Using point-scale flux-tower measurements, Williams et al. (2012) supports the finding of Oudin et al. (2008), by showing generally higher E over grassland when compared to forest. However, Peel et al. (2010) argued that results are potentially more diverse than shown by Oudin et al. (2008) if the set of catchments represents all climate zones.

Estimating the n-parameter of Choudhury’s equation (Choudhury, 1999) by using Porporato’s model (Porporato et al., 2004), the BCP model established by Donohue et al. (2012) provides interesting insights on the sensitivity of runoff on rooting depth. Donohue et al. (2012) found a generally high sensitivity of runoff on changes in P within the highly arid Murray-Darling basin and relatively small, but substantial sensitivity on changes in rooting depth. However, within the highest yield zones of the basins, the sensitivity on rooting depth was larger. In the framework of Fu (1981) and Zhang et al. (2004), Shao et al. (2012) identified four factors being of major importance, including that in flat catchments an increase in vegetation coverage leads to an increase in the parameter $\omega$. However, Li et al. (2013) determined a significant influence of long-term averaged annual vegetation coverage based on remotely sensed Normalized Density Vegetation Index (NDVI) within 26 major global river basins larger than $300,000km^2$. The results of Li et al. (2013) partly contradict Donohue et al. (2010), since the determined relationship does not apply within smaller catchments (less than $50,000km^2$). Within a neural network framework, Xu et al. (2013) developed a model to estimate the scatter as a function of several geolocation, topographic and vegetative indices.

**Topographic control**  Topographic characteristics within a catchment potentially alter runoff generation. Yang et al. (2007) analysed the influence of catchment average slope, showing that steep catchments basically tend to generate a smaller n-parameter in Choudhury’s equation, resulting in enhanced Q versus suppressed E. Yokoo et al. (2008) found in their assessment that seasonality effects on P and Ep, which themselves impact the mean annual
1.4. THE BUDYKO FRAMEWORK

water balance (following Milly (1994) ), are stronger in flat rather than in steep basins if surface runoff (and not subsurface runoff) is dominating. Both Zhang et al. (2004) and Shao et al. (2012) considered relief ratio, calculated as total catchment relief (i.e., the difference between maximum and minimum elevations) and the longest flow path, to be of importance for estimating the $\omega$-parameter of Fu’s equation. However, while in the approach of Zhang et al. (2004) relief ratio was not identified to be of significant importance, Shao et al. (2012) diagnosed relief ratio among 4 other measures to be of primary importance. The interaction between relief ratio and average storm depth shows that larger (smaller) average storm depth in flat (hilly) catchments enhances runoff. Further, the interaction between relief ratio and forest coverage shows that in flat catchments an increase in vegetation coverage leads to an increase in $\omega$, suggesting enhanced E. Xu et al. (2013) explored the importance of several local and global geolocation parameters, including slope gradient, slope aspect, compound topography index (CTI). Depending on the set of catchments, the slope estimates were found to explain a significant fraction of the observed variance. By assessing topographic controls at local scales, Nippgen et al. (2011) found topographic characteristics to be more important than climatic control in snowmelt-dominated regions, questioning the applicability of the Budyko framework in such regions.

**Seasonality** Seasonal variations of the input variables potentially control the Budyko curve and are assessed in numerous studies. Budyko (1974) himself mentioned that systematic deviations from the original curve could be related to the interaction of seasonality between $E_p$ and $P$. As assessed in a variety of studies, observations show that catchments with in-phase seasonal variations of monthly $E_p$ and $P$ tend to plot above the original Budyko curve, whereas catchments with out-of-phase seasonalties tend to plot below the original curve (Milly, 1994; Potter et al., 2005; Hickel and Zhang, 2006; Yokoo et al., 2008; Gerrits et al., 2009; Gentine et al., 2012). Using his stochastic model, Milly (1994) was able to reproduce these seasonal effects and also suggested a possible explanation, being supported by Gentine et al. (2012). That is, that vegetation potentially adapts to a large phase difference between $E_p$ and $P$ and thus, under dry conditions, water could be accessed from greater depths.

**Other controls** Based on Milly (1994), Porporato et al. (2004) and Donohue et al. (2012) found an upward shift of the Budyko framework for increasing soil-specific rooting depth. Yang et al. (2007) argued that a decreasing infiltration capacity or an increasing relative soil water storage lead to an upward shift of the Budyko curve. Based on Milly (1994), Yokoo et al. (2008) found strong impacts on the mean annual water balance if seasonal variations in $P$ and $E_p$ are out of phase. These seasonality effects are, however,
related to topographic and soil properties. In well drained soils with predominant surface runoff (and not subsurface runoff), seasonality effects are higher. However, if infiltration rate excesses surface runoff, these findings are not valid, suggesting that the impact of soil types is very important and requires comprehensive assessments in addition to the effects of soil storage capacity alone.

Milly (1994) first recognized the importance of storminess regarding the partitioning of $P$ into $E$ and $Q$. He defined storminess as the mean number of $P$ events per year occurring for the same amount of annual $P$, further noting, that a few heavy rainfall events will potentially generate larger $Q$ than more frequent, but small rain events. Even though the methodology of Porporato et al. (2004) and Milly (1994) is different, also Porporato et al. (2004) found an increase in mean annual runoff with increasing storminess. Interesting to note is that in their assessment both storminess and effective rooting depth counteract one another, a result also supported by Donohue et al. (2012).

Effects of groundwater control have been examined in studies by O’Grady et al. (2011) and Istanbulluoglu et al. (2012). They showed that inconsistencies with the Budyko hypothesis that are found to take place in groundwater-controlled catchments could be addressed by considering storage changes estimated from basin-averaged groundwater-table fluctuations.

The influence of plant-available soil water storage has been discussed in several assessments, however, the potential control mechanisms related to interception or snow storage, have only been examined in single studies. Gerrits et al. (2009) obtained a relationship similar to the Budyko curve by developing a model based on simple representations of interception and transpiration processes. Berghuijs et al. (2014) found that $Q$ also decreases for catchments experiencing a shift towards less precipitation falling as snow under climate change.

**Hybrids/combinations of controls**

Pioneering the work on multiple controls acting simultaneously on the partitioning of $P$ between $E$ and $Q$, Milly (1994) introduced a stochastic model framework including seven dimensionless parameters representing different physical characteristics. Milly (1994) identified (i) aridity index itself to be most important. Other factors were (ii) the ratio of the spatially averaged plant-available soil water-holding capacity to annual mean $P$, with a large ratio potentially promoting $E$ and dampening $Q$. Besides (iii) storminess (large storminess implying larger $Q$) and (iv) $E_p$ itself, also seasonality effects of (v) $P$ and (vi) storminess (storm arrival rate) were examined by Milly (1994). Milly (1994) acknowledged that variations around the original Budyko curve are significantly related to out-of-phase seasonality effects of $P$ and $E_p$. Additionally, (vii) the shape parameter of the gamma distribution representing the spatial variability of storage capacity was considered, but it
was identified to be of insignificant importance for predicting $Q$.

By deriving a rather simple stochastic model of soil moisture dynamics, Porporato et al. (2004) identified a relationship very similar to Budyko’s framework. The model of Porporato et al. (2004) includes another parameter, which is the ratio of effective rooting depth and storminess. As earlier mentioned, the approach of Porporato et al. (2004) was adapted by Donohue et al. (2012) to introduce a flexible Budyko model (referred to as Budyko-Choudhury-Porporato, or BCP model) dependent on storminess, effective rooting depth and soil porosity.

A few studies (Zhang et al., 2004; Yang et al., 2007; Shao et al., 2012; Xu et al., 2013) attempted to identify the main controls on the free parameter $\omega$ in Fu’s equation (Fu, 1981; Zhang et al., 2004). Besides $E_p/P$ being the most important factor controlling the partitioning of $P$ into $E$ and $Q$, Zhang et al. (2004) tested the importance of several catchment characteristics performing a stepwise regression using Fu’s equation. However, only three factors, storminess, plant available water capacity, and storm arrival rate, passed their test procedure and were thus considered to contribute significantly new information to predict annual $E$.

Following a similar, but more sophisticated approach, Shao et al. (2012) identified four important controls on $\omega$. These are, (i) the phase difference between $P$ and $E_p$, with large phase difference resulting in more $Q$, (ii) the interaction between storminess and the coefficient of variation in precipitation, which for certain combinations of values, reduces $\omega$, (iii) the interaction between storminess and relief ratio, with reduced $\omega$ resulting from either steep or flat catchments with high storminess, and (iv) the interaction between relief ratio and forest coverage, indicating that the effect of increasing $\omega$ with increasing forest coverage is less pronounced for steep catchments.

Yang et al. (2007) found that $\omega$ is significantly correlated to relative infiltration capacity (defined as the ratio of saturated hydraulic conductivity to mean precipitation intensity), relative soil water storage (defined as the ratio of plant-available water capacity to mean annual $E_p$), and the average slope of the respective catchment area. In a later assessment, (Yang et al., 2009) identified vegetation coverage to be of greater importance than relative soil water storage.

Xu et al. (2013) argued that both global (latitude, longitude, and elevation) and local (vegetation, slope gradient, catchment area, etc.) factors play an essential role in the control of the water-energy balance within the Budyko framework. They further suggest to estimate $\omega$ independently from climatic factors.

By combining seasonality estimates of $P$ and $E_p$ and various landscape characteristics, Yokoo et al. (2008) found that combinations of landscape properties resulting in good drainage abilities increase the amplitude of seasonality effects on the mean annual water balance.
Conclusions

The short review provided in this section illustrates that the Budyko framework is the subject of intense ongoing research, but until present no conclusive assessment on processes determining the basic characteristics of the Budyko curve was reached. In the present study, we are aiming to enhance the framework by addressing limitations of the Budyko hypothesis (in Chapters 4 and 5), rather than contributing to the large, but not yet (and potentially never) comprehensive amount of studies assessing potential controls. By doing so, a possibly more efficient use of the Budyko framework for future fundamental research and applications is enabled and we further argue that framework should preferably be used for conceptualized, rather than process-based assessments.

Nonetheless, the Budyko framework is a simple and powerful tool to assess the partitioning of precipitation into evapotranspiration and runoff, comprising knowledge of more than a century of hydrological observations and experience (Roderick et al., 2014). It is therefore used for a variety of different purposes, like e.g. assessing changes in the catchment water balance as a function of climate change (Roderick and Farquhar, 2011; Renner et al., 2012; Renner and Bernhofer, 2012; van der Velde et al., 2013; Destouni et al., 2013; Jaramillo and Destouni, 2014) or to predict water availability in ungauged basins (Blöschl et al., 2013; Li et al., 2013; Xu et al., 2013). In the present thesis the framework is also used as a validation tool (Chapter 2).

1.5 Aims and outline

The main topic of the present introduction was to highlight challenges associated with the identification of hydroclimatological changes within the climate system. It was further emphasized that both assessments on past and present changes are subject to potentially large uncertainties. These uncertainties arise from different sources which could be summarized into data uncertainty due to the variety of data products, and methodological uncertainty due to the large amount of possible techniques and methods used to estimate and derive certain climate variables and indices. For this reason, I outlined that results regarding hydroclimatological changes are diverse and partly also conflicting. It is further important to note that the present thesis concentrates mainly on changes regarding mean climatic conditions rather than on studying changes in climate extremes.

The overall focus of the first part of the present thesis lies on the assessment of changes in hydroclimatological conditions over land for both the recent past (second half of the 20th century) and the future (until 2100) by using comprehensive approaches to carefully evaluate and address the underlying uncertainties. The final results should reflect the current knowledge on hydroclimatological changes over land, and areas without robust signals
are consequently identified and excluded. Regarding changes in dryness or wetness, potentially false interpretations also arise from an oversimplification of past and anticipated trends, summarized in short catchphrases and paradigms. Among such paradigms, the most well-known and already introduced ‘dry gets drier, wet gets wetter’ paradigm is explicitly evaluated using the obtained robust results for both past and future drying/wettening (Chapters 2 and 3).

This thesis also presents a new approach to validate data products by using the Budyko framework. The Budyko framework is widely accepted as a simple and powerful tool to assess the partitioning of precipitation into evapotranspiration and runoff. Yet, major disadvantages are (i) its highly nonlinear geometric nature and (ii) its limitation to steady-state conditions preventing the use of the Budyko model at shorter than seasonal and technically also other than catchment scales (Roderick et al. (2014) was however showing that the Budyko model is also valid on gridbox-scales). Both issues are separately addressed in Chapters 4 and 5 to enhance the potential and to enable a more concise future use of the Budyko framework.

Research Questions The main aims of this thesis are outlined by the following research questions

- What is the current knowledge about past and anticipated hydroclimatological changes, when data and methodological uncertainty is extensively taken into account.

- Does the ‘dry gets drier, wet gets wetter’ paradigm provide a valid summary of hydroclimatological changes?

- Is it possible to establish a probabilistic Budyko framework that accounts for the nonlinearity of the Budyko curve and to statistically represent the observed scatter within the Budyko space.

- Is it possible to derive a formulation of the Budyko curve for non-steady-state conditions?

The present thesis consists of six chapters and 4 appendices. The main part (Chapters 2-5) consists of four published articles. These chapters are included as individual scientific contributions and each contains an abstract, introduction, main part and conclusions. The chapters are outlined as follows:

- Chapter 2: Global assessment of trends in wetting and drying over land (Greve et al., 2014, Nature Geoscience) By using a large variety of available data products and by preselecting physically-consistent dataset combinations, robust trends in wetting and drying
over land within the 2nd half of the 20th century are identified and the ‘dry gets drier, wet gets wetter’ paradigm is validated.

- Chapter 3: Comprehensive assessment of future changes in water availability and aridity (Greve and Seneviratne, 2015, Geophysical Research Letters) By using an ensemble of CMIP5 climate models, robust changes in projected hydroclimatological conditions over land within the 21st century are identified and the suitability of ‘dry gets drier, wet gets wetter’ paradigm to characterize future projections is assessed.

- Chapter 4: Introducing a probabilistic Budyko framework (Greve et al., 2015, Geophysical Research Letters) By assuming that the combined influence of landscape and climate characteristics on water availability follows an arbitrary probability distribution, a probabilistic Budyko framework is introduced and potential applications for its future use are provided.

- Chapter 5: The Budyko framework beyond stationarity (Greve et al., 2015, Hydrology and Earth System Sciences Discussion) By relaxing the stationarity assumption in the derivation of a widely-used Budyko formulation, a new two-parameter framework is analytically derived and evaluated against standard data products at monthly time scales.

- Chapter 6: Conclusions and outlook.
Part I

Past and future hydroclimatological changes over land
Global assessment of trends in wetting and drying over land

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Abstract Assessments of observed continental dryness trends yield contradicting results since they are substantiated using diverse methodologies and data sources (Seneviratne et al., 2012; Burke and Brown, 2008; Dai, 2011; Sheffield et al., 2012; Orlowsky and Seneviratne, 2013). In this context, the ‘dry gets drier, wet gets wetter’ paradigm is often being used as a simplifying summary of anticipated (Held and Soden, 2006; Chou et al., 2009; Durack et al., 2012) as well as observed water-related climate changes over land (Allan et al., 2010; Seager and Vecchi, 2010; Durack et al., 2012; Liu and Allan,

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2013; Chou et al., 2013), although it is mostly based on oceanic data (Held and Soden, 2006; Durack et al., 2012). Here we provide a comprehensive and robust assessment of historical land dryness changes by analyzing more than 300 combinations of various hydrological datasets. The realism of each combination is benchmarked against the Budyko curve (Budyko, 1974; Fu, 1981; Zhang et al., 2004; Donohue et al., 2007; Roderick and Farquhar, 2011; Li et al., 2013; Roderick et al., 2014) and those combinations performing well are used for trend analysis. Our results confirm previously identified hot spots of changing dryness (Dai, 2011; Seneviratne et al., 2012; Sheffield et al., 2012), but also highlight that over large extents of global land area (75.4%) robust dryness changes cannot be detected. Within the 24.6% land area fraction with robust changes, only the minority (10.8%) confirms the ‘dry gets drier, wet gets wetter’ paradigm. Of the remaining regions 9.5% display opposite changes (i.e. wettening dry areas and drying wet areas) and another 4.3% display drying/wetting in transitional climate regions. In particular, some humid regions have experienced increasing dryness with potential consequences for a wide range of socio-economic sectors (Piao et al., 2010; Hoekstra and Mekonnen, 2012).

2.1 Introduction

Changes in the hydrological conditions of the land surface have major impacts on society (Piao et al., 2010; Hoekstra and Mekonnen, 2012). The ‘dry gets drier, wet gets wetter’ (DDWW) paradigm has become a standard catchphrase frequently used in studies and assessments of historical and future climate change (Held and Soden, 2006; Chou et al., 2009; Allan et al., 2010; Seager and Vecchi, 2010; Liu and Allan, 2013). However, remaining large uncertainties in assessments of past changes (Burke and Brown, 2008; Dai, 2011; Seneviratne et al., 2012; Sheffield et al., 2012; Liu and Allan, 2013; Orlowsky and Seneviratne, 2013) and the fact that historical assessments of the DDWW paradigm are based on oceanic evidence (Held and Soden, 2006; Durack et al., 2012; Roderick et al., 2012, 2014), require a careful reevaluation of its validity over land. The choice of data constitutes an essential source of uncertainty, due to the large number and diversity of existing hydrological datasets (Seneviratne et al., 2012; Mueller et al., 2011; Sheffield et al., 2012). Here we circumvent these issues through the analysis of an unprecedentedly large selection of evapotranspiration (\(E\)), precipitation (\(P\)) and potential evaporation (\(E_p\)) datasets and their combinations. Another issue lies in the use of different measures for changes in dryness or wetness, which often only take single components of the water balance into account (Burke and Brown, 2008; Vicente-Serrano et al., 2009; Seneviratne et al., 2012; Sheffield et al., 2012). In addition, also the definition of ‘dry’ vs ‘wet’ regions can be problematic. For instance, they cannot be characterized with
negative vs positive $P - E$ values over land (unlike for ocean areas (Held and Soden, 2006)) since $P - E$ is overwhelmingly positive on continents (see Appendix A). We address these issues here by applying an improved metric that is more relevant for climate impacts to global land regions for the historical period 1948-2005. Thereby, we directly investigate dryness changes in the phase space spanned by the water balance at the land surface ($P - E$) and by considering potential hydroclimatic regime shifts in the aridity index $E_p/P$. ‘Dry’ vs ‘wet’ climate regimes are based on well-established definitions from the hydrological literature (Middleton et al., 1997).

In a first step, the combinations of $E$, $P$ and $E_p$ datasets are evaluated for physical consistency using the Budyko framework (Budyko, 1974). In order to maximize the number of available datasets and, in particular, to include a sufficient number of observations-based datasets, we choose the 1984-2005 time frame for validation. Over this period, we evaluate all combinations against the Budyko framework (Budyko, 1974; Fu, 1981; Zhang et al., 2004; Donohue et al., 2007; Roderick and Farquhar, 2011; Li et al., 2013; Roderick et al., 2014), which provides a well-established and both empirically and theoretically solid functional relationship relating the evaporative index $E/P$ to the aridity index $E_p/P$. This approach permits a direct evaluation of the individual combinations of $E$, $P$ and $E_p$ datasets, without evaluating single datasets first. The aridity index captures the competing effects of land water supply and atmospheric water demand, with the former (latter) being dominant for $E_p/P > 1$ ($E_p/P < 1$). We use Fu’s formulation of Budyko’s relationship (Fu, 1981),

$$\frac{E}{P} = 1 + \left( \frac{E_p}{P} \right) - \left( 1 + \left( \frac{E_p}{P} \right)^\omega \right)^{\frac{1}{\omega}}, \quad (2.1)$$

which includes the free parameter $\omega$, being related to the climatological Normalized Density Vegetation Index (NDVI) (Li et al., 2013) and thus accounts for vegetation influences (Donohue et al., 2007) (see Detailed Methods). Both ratios are computed from climatological annual averages of the 1984 - 2005 period. Note that this adjusted Budyko curve is still a rough approximation of the relation between $E/P$ and $E_p/P$, which further depends on processes and parameters related to soil moisture dynamics, soil texture, land use and carbon exchange.

## 2.2 Data and methods

### 2.2.1 Data

We use 17 global $E$ (Mueller et al., 2011, 2013; Sitch et al., 2013) and 6 observations-based global $P$ datasets together with 21 estimates of $E_p$ for the evaluation, resulting in a total of 2142 combinations for the 1984-2005 period (see Detailed Methods and Appendix A for further information on all
Figure 2.1: Vegetation adjusted Budyko framework. a) Point cloud of climatological $E/P$ vs. $E_p/P$ from all grid points, taken from one combination of $E$, $P$ and $E_p$ datasets (NOAH, CRU, Princeton $E_p$) within the Budyko space. Black lines illustrate the demand ($E < E_p$) and supply limit ($E < P$). The Budyko curve (dark grey) in its original formulation ($\omega = 2.6$) does not account for land surface properties. Fu’s equation adjusted to climatological NDVI of ca. 0.8 over Amazonia (dark yellow) and ca. 0.2 over Africa (red) displays a better fit to the corresponding gridpoints. b) Climatological NDVI for the 1984 to 2004 period. Red (light green) color denotes gridpoints with NDVI values of 0.2 (0.8) over Africa (Amazonia) as in a).
2.2. DATA AND METHODS

Figure 2.2: Budyko validation of hydrological dataset combinations for the 1984-2005 period. Boxplots of all RMSwEs related either to a) an individual $E$, b) an individual $P$ dataset or c) the $E_p$ estimates. Datasets not spanning the 1948-2005 period are marked with a star. Colors for the $E$ datasets denote the different classes (Mueller et al., 2011): observations-based ‘diagnostic’ datasets (orange), LSMs with various forcings (green), LSMs from the TRENDY TR project (Sitch et al., 2013) (blue), reanalysis (yellow). Dashed vertical lines illustrate the absolute minimum, the overall median and absolute maximum RM-SwE (from left to right). See text and Appendix A.
good trade-off between a sufficient subset of dataset combinations and a long enough time period to analyse changes. We use 7 $E$ datasets with median RMSwE below the overall median (see Fig. 2.2) spanning the longer period in combination with 4 $P$ and 11 $E_p$ data estimates. Note that the corresponding validation of these datasets for the longer period yields consistent results (see Appendix A).

To analyse long-term hydrological changes we compare differences between the 1948-1968 and 1985-2005 periods, considering both changes in water availability (evaluated from the comparison of $\Delta P$ and $\Delta E$) and changes in climate aridity/humidity (evaluated from the comparison of $\Delta P$ and $\Delta E_p$). We compute climatologies to be consistent with previous studies (Held and Soden, 2006; Durack et al., 2012) and the Budyko framework. Note that our results are not qualitatively affected by the exact definition of these time periods (see Appendix A). Based on this approach, we identify drying trends in water availability in regions with $\Delta E > \Delta P$ (and respectively wetting trends in regions with $\Delta E < \Delta P$), and regime shifts towards more arid (humid) conditions in regions with $\Delta E_p > \Delta P$ ($\Delta E_p < \Delta P$). By doing so we give consideration to the different hydroclimatological characteristics of the land surface in comparison to the ocean, as the available water is limited there by both water storage and water supply. Thus both changes in the water supply ($P$) and storage depletion/accumulation (changes in $E$ and $E_p$) need to be jointly considered.

For each grid point, we obtain 28 (77) combinations for $\Delta E$, $\Delta P$ ($\Delta E_p$, $\Delta P$) which we plot in the respective phase spaces (see Fig. 2.3). The deviation of a point cloud from the line of no change (the Identity function) is quantified by the Mahalanobis distance and significance is assigned using the F-distribution (see Detailed Methods).

### 2.3 Hydroclimatological trends

A striking feature is the large fraction (75.4%) of land area with non-significant changes, which is primarily a result of data uncertainty although interannual and decadal variability could also play a role (Orlowsky and Seneviratne, 2013).

Areas undergoing significant changes ($p < 0.05$) towards drier/wetter conditions regarding combinations of ($\Delta P$, $\Delta E$), ($\Delta P$, $\Delta E_p$), or both are shaded in Fig. 2.4a. Changes towards more arid conditions (red/orange) are found in many parts of Africa, especially in the Sahel and East Africa, East Asia, East Australia and partly in the western Mediterranean and Northeast Brazil. In contrast, drying trends in the northern Mediterranean and small parts of the Sahel are due to changes in the water availability (pink/green). Note that the identified changes in dryness in the Sahel region are unlikely to have been due to changes in greenhouse gas forcing, as there is a wettening
2.4. VALIDATING THE DDWW PARADIGM

Figure 2.3: Detection of robust dryness changes. Point clouds of $\Delta P$ against $\Delta E$ (blue) and $\Delta E_p$ (orange) for a particular grid point ($8.25^\circ N, 8.75^\circ E$). To each point cloud with its corresponding center of mass ($\mu$) we fit a bivariate normal distribution. Values above the identity line (line of no change) correspond to drying hydroclimatic conditions. The Mahalanobis distance is measured to the identity line and significance is assigned following a Fisher distribution (see Detailed Methods). This example shows a significant shift towards drier conditions regarding the land water balance and in terms of hydrological regime shift (Note that $\Delta P_{CRU} = -0.2538$ and $\Delta P_{REC/L} = -0.2541$ are very similar and thus almost not distinguishable). Units are mm/day.

in recent years (Seneviratne et al., 2012) and analyses have suggested that changes in large-scale circulation patterns due to aerosol forcing may be relevant for these (Hwang et al., 2013). In addition, local changes in dryness are also strongly influenced by changes in large-scale circulation patterns (e.g. decadal changes in El Nino Southern Oscillation for tropical rainfall over land (Liu and Allan, 2013)) Significant drying trends in both the water availability and hydrological regime are sparse and primarily found in parts of West Africa. Wetting trends are located in Eastern North America, parts of South America and Australia. These results confirm previous findings regarding long-term changes (Seneviratne et al., 2012), such as e.g. drying trends in the Mediterranean and East Asia, and wetting in Eastern North America. They also highlight changes over East Africa (drying) and parts of South America (wetting).

2.4 Validating the DDWW paradigm

To evaluate the DDWW paradigm in areas undergoing significant changes, every grid point is additionally classified as either arid ($E_p/P > 2$) or humid ($E_p/P < 2$) over the 1948-1968 period (Middleton et al., 1997). Regions not significantly classified as either arid or humid are denoted as transitional climate regimes (Seneviratne et al., 2012). The classification of each grid
Figure 2.4: Investigating the DDWW paradigm. a) Significant drying/wetting trends computed at the grid box level. Dark red (dark blue) denotes a significant change towards drier (wetter) conditions both regarding the land water balance and hydrological regime shifts. Red/orange shows a shift towards more arid conditions. Drying due to changes in the land water balance only is depicted by green/pink color. b) Distribution of arid (orange) to humid (blue) areas within the period from 1948-1968. Beige colors denote transitional areas where no significant attribution is possible. c) Comparing the changes in a) with the hydrological conditions in b) yields an evaluation of the ‘dry gets drier, wet gets wetter’ paradigm. Red/dark blue colors indicate regions where the paradigm is found to be valid. Humid areas getting drier (orange) are widely found.
point uses the same Mahalanobis distance-based approach as for the drying trends (see Fig. 2.3 and Detailed Methods for more details). The resulting pattern (see Fig. 2.4b) is in good agreement with the commonly used standard climate-classifications of Köppen-Geiger (Peel et al., 2007).

A systematic comparison of both changes and climatological hydrological conditions of the early 1948-68 period, allows us to evaluate the DDWW paradigm (see Fig. 2.4c) for historical changes. The paradigm is proved to be invalid in the major fraction of the area with change. This particularly applies to large areas classified as humid south of the Sahel, in Central and Eastern Africa, north of the Mediterranean and parts of East Asia, which all experienced significant drying. The area of wetting dry regions on the other hand is small. Note that significant changes are also found in transitional regions, generally towards drier conditions, like e.g. in East Asia, the western Mediterranean, small parts of Eastern Australia and Africa. Altogether the area fraction where the DDWW paradigm is not valid (13.8%) is larger than the fraction in which it is confirmed (10.8%), highlighting that it does not apply to historical changes at annual time scales over land. However, changes at seasonal scales are not analyzed in this study and may take place in some regions (Chou et al., 2009, 2013).

2.5 Conclusions

Our results emphasize that one should be careful when relying on simplifying statements such as the DDWW paradigm for assessments on historical dryness changes, which are potentially misleading as they do not fully account for the complexity of the underlying system. Note that several previous studies pointing to the DDWW paradigm include ocean areas in their analysis (Held and Soden, 2006; Chou et al., 2009; Durack et al., 2012; Allan et al., 2010; Chou et al., 2013; Liu and Allan, 2013). While the DDWW paradigm possibly holds over the ocean (but using definitions of ‘dry’ and ‘wet’ regimes which are not applicable to land areas), our results clearly show that the DDWW is an oversimplification over land. In addition, previous findings (Held and Soden, 2006; Chou et al., 2009; Liu and Allan, 2013) argue that patterns of $P - E$ will be enhanced due to increased moisture fluxes, implying solely a wet gets wetter response over land (although our analysis does also not confirm this feature for historical data). These issues were noted before (Held and Soden, 2006; Roderick et al., 2014), but are not addressed in the public discourse and so far no attempts were made to account for the different hydroclimatological conditions over land. Also note that previous studies assess seasonal (Chou et al., 2009, 2013) and/or large-scale/zonal changes (Held and Soden, 2006; Chou et al., 2009; Durack et al., 2012; Allan et al., 2010; Chou et al., 2013; Liu and Allan, 2013), rather than mean annual changes at regional scales. Given the importance of regional dryness changes...
for socio-economic sectors, our results highlight that studies on changes in hydroclimatological conditions must not rely on single variable datasets and dryness metrics in order to adequately assess the underlying uncertainties.

2.6 Detailed methods

2.6.1 Evapotranspiration and precipitation datasets

The $E$ data sets are subdivided into three categories (Mueller et al., 2011, 2013): 1) ‘diagnostic datasets’, which are primarily derived from observations, 2) Land Surface Model (LSM)-based estimates driven by observations-based forcing and 3) reanalysis estimates. $P$ data sets are either derived from rain gauge observations only, or from rain gauges in combination with satellite-derived estimates.

2.6.2 Potential evaporation estimates

We use here 3 common methods of differing complexity to determine $E_p$. Priestley-Taylor with a constant (PTc) or with a varying alpha parameter (PT) includes net radiation ($R_n$). The widely used method by Penman-Monteith (PM) additionally considers influences of vegetation and aerodynamic properties. $E_p$ is also estimated directly from $R_n$ (by dividing $R_n$ with the latent heat of vaporization $\lambda$). By employing datasets of radiation and temperature, together with a pre-compiled ‘dry’ and ‘wet’ PM dataset (Sheffield et al., 2012), 21 estimates of global $E_p$ are used. Several studies have shown that temperature-based $E_p$ estimates are not suitable for trends (Sheffield et al., 2012), and we thus do not use such estimates here. Nonetheless, we note that the results are not strongly affected if these are included (see Appendix A). Further information on all datasets and methods is provided in the Appendix A.

2.6.3 Budyko evaluation

In order to account for vegetation influences, the Budyko curve (Eq. 1) is adjusted using climatological NDVI (Li et al., 2013), which relates linearly to the free parameter $\omega$ in Eq. 1.

$$\omega = 2.36 \cdot \left( \frac{\text{NDVI} - \text{NDVI}_{\min}}{\text{NDVI}_{\max} - \text{NDVI}_{\min}} \right) + 1.16. \quad (2.2)$$

The RMSwE of a particular cloud of $n$ points within the Budyko space is then calculated as,

$$\text{RMSwE} = \sqrt{\frac{\sum_{i=1}^{n} (w_i \cdot D_i)^2}{n}}, \quad (2.3)$$
with $w_i$ being the individual weight of point $i$. The $i$th deviation $D_i$ is the Euclidean distance between point $i$ and the adjusted Budyko curve, accounting for errors in both $E/P$ and $E_p/P$ at the same time. The weight $w_i$ is calculated as

$$w_i = 1 + \sqrt{s_i/1},$$

(2.4)

with $s_i = 0$ for all points within the limits ($E/P \leq 1$ and $E \leq E_p$). Outside the limits we assign the Euclidean distance between point $i$ and the limits to $s_i$. Thus, $w_i$ is increasing relatively fast for small overshoots, but more slowly for large overshoots in order to reduce the influence of possible outliers. A perfect fit of a point cloud to the adjusted Budyko curve results in a zero RMSwE.

### 2.6.4 Mahalanobis distance and significance

In order to measure distance and its significance of a point cloud from the no-change line within the ($\Delta P$, $\Delta E$) and ($\Delta E_p$, $\Delta P$) spaces, respectively, we calculate the Mahalanobis distance $D_M$. $D_M$ is based on the covariance matrix $\Sigma$ which provides a joint measure of data uncertainty in both variables of the respective point cloud,

$$D_M(\mu, Id) = \sqrt{(\mu - Id)^T \Sigma^{-1} (\mu - Id)},$$

(2.5)

where $\mu$ denotes the center of mass and Id the identity function (line of no change). Since Id and the point cloud of the data estimates are completely independent, the distance distribution approximately follows an F distribution

$$\frac{npD_M^2}{n-p} \sim F(p, n-p),$$

(2.6)

where $n$ denotes the number of data points and $p$ the degrees of freedom ($p = 2$ in a two-dimensional case). Significance at the 5% level is thus assigned for $n = 28$ combinations of $E$ and $P$ datasets if $D_M^2 \gtrsim 1.5$ and for $n = 44$ combinations of $E_p$ and $P$ datasets also if $D_M^2 \gtrsim 1.5$.

### 2.6.5 Classification of hydrological conditions

Aridity (or humidity, respectively) is assigned at the grid-box level if the Mahalanobis distance between the cloud of ($P, E_p$) data points and the $2 \cdot Id$ line ($E_p/P = 2$) is significant ($p < 0.05$) following the above-mentioned F-distribution, and the center of mass lies above (below) the $2 \cdot Id$ line. Regions not significantly classified as either arid or humid hydroclimatological conditions are denoted as transitional. Of all (non-missing) global land area, ca. 59% is classified humid, whereas ca. 25% is arid and 16% is transitional. It
is important to note, that many hyperarid regions (like e.g. the Sahara) have missing data.

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Assessment of future changes in water availability and aridity

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**Abstract** Substantial changes in the hydrological cycle are projected for the 21st century, but these projections are subject to major uncertainties. In this context, the ‘dry gets drier, wet gets wetter’ (DDWW) paradigm is often used as a simplifying summary. However, recent studies cast doubt on the validity of the paradigm and also on applying the widely used $P - E$ (precipitation-evapotranspiration) metric over global land surfaces. Here we show in a comprehensive CMIP5-based assessment that projected changes in mean annual $P - E$ are generally not significant, except for high-latitude regions showing wetting conditions until the end of the 21st century. Significant increases in aridity do occur in many subtropical, but also adjacent humid regions. However, combining both metrics still shows that ca. 70% of all land area will not experience significant changes. Based on these findings we conclude that the DDWW paradigm is generally not confirmed for

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projected changes in most land areas.

3.1 Introduction

Changes in dryness and water availability are projected to be large in many regions, with major impacts on a wide range of socio-economic sectors. However, major uncertainties regarding both past and especially future drought assessments (Sheffield et al., 2012; Seneviratne et al., 2012; Orlowsky and Seneviratne, 2013) hinder a straightforward communication of projected changes to the public and policymakers.

A commonly used simplifying summary of projected changes in the global water cycle is that ‘dry regions become drier and wet regions become wetter’, yet over land this is not applicable to changes in hydro-climatological conditions relevant to water availability for human society (e.g. Sun et al., 2012; Roderick et al., 2014; Greve et al., 2014, hereafter G14).

One first issue, as highlighted by G14 and Roderick et al. (2014), is a deficiency of the widely used $P - E$ metric (e.g. Held and Soden, 2006; Dai, 2013; Liu and Allan, 2013) to assess climatic regimes over land. Following the notation of Held and Soden (2006), $P - E > 0$ implies a ‘wet regime’ and $P - E < 0$ a ‘dry regime’ at climatological time scales. However, over land $E$ is limited by the amount of water supplied through $P$. Consequently all land area is defined as wet ($P - E > 0$) according to this metric, which is certainly misleading. Held and Soden (2006) mentioned and discussed these issues in their study and the zonally averaged $P - E$ signal pointing towards a DDWW response is clearly ocean-dominated (see Fig. 3.1) since changes in $P - E$ over land are generally not significant. This issue was also recently highlighted for historical trends in G14 and pointed out for future assessments by Roderick et al. (2014).

Although observations-based datasets do not suggest that the DDWW holds for the historical time period (e.g. G14), it has not yet been investigated whether it holds for the future when considering suitable hydrological regimes definition over land. Hence, a careful reevaluation of the DDWW paradigm for climate projections over land is required. We note that we focus here on annual changes in the water cycle, and not on contrasting changes in wet and dry season precipitation (e.g. Liu and Allan, 2013; Chou et al., 2013). This study aims to assess future projected changes in water availability and aridity within the physically-based framework of G14.

3.2 Data and methods

Changes in hydroclimatological conditions are examined using $P$, $E$ and net radiation $R_n$ estimates of an ensemble of 30 models from the Coupled Model Intercomparison Project Phase 5 (CMIP5). All data are bilinearly regridded
Figure 3.1: The zonal mean $\Delta(P-E)$ (1980-99 vs 2080-99, top panel) and $P-E$ of the present climate (1980-99, middle panel) from the ensemble mean of 35 CMIP5 model runs (black), for ocean grid points only (blue) and for land grid points only (green). The shading denotes the ensemble standard deviation. The overall result (black line) corresponds very well to the finding of Held and Soden (2006). However, the distinction between land and ocean grid points reveals fundamental differences. Over land the zonal mean drying trends are, if any, very small and not significant in subtropical regions. The figure clearly shows that the overall signal (Held and Soden, 2006) is dominated by the ocean signal (which makes sense regarding the unequal distribution of zonal land area vs. ocean area, bottom panel). The figure further shows that $P-E > 0$ over land and thus technically all land regions are wet (middle panel). (Figure taken from Appendix A)
to a unified 2.5 × 2.5° grid and climatological means are computed for the 1980-1999 (using historical data) and 2080-2099 (using data estimated under the RCP8.5 scenario) time periods. Here we use net radiation to define the energy constraint on $E$, usually referred to as potential evapotranspiration $E_p$, unlike in G14, where $E_p$ formulations were used for the historical assessments. Thus, we assume $E_p = R_n/\lambda$ (with $\lambda$ denoting latent heat of vaporization). We chose this definition of $E_p$ for two reasons: (i) In contrast to $R_n$, $E_p$ itself is not part of the standard output in CMIP5; and (ii) we expect other (especially temperature-based) approaches to estimate $E_p$ to be less robust under substantially different climatic conditions occurring under strong climate change (Milly, 1992; Shaw and Riha, 2011; Milly and Dunne, 2011). An analysis performed using the Priestley-Taylor method (Priestley and Taylor, 1972) to estimate $E_p$ is provided in Appendix B.

### 3.3 Trends in P-E

Considering 20-year climatologies, the partitioning of annually-averaged $P$ into $E$ and runoff $Q$ over land follows the simplified water balance $P = E + Q$ since the time derivative of the storage term is considered to be negligibly small in comparison. Hence, the assessed metric $P - E$ is equal to $Q$ and is basically a measure of water availability when examined from a land hydrological viewpoint. However, P-E is an incomplete metric to define present conditions of dryness at the land surface for several reasons. First, negative P-E values are impossible on land because $E$ is constrained by the available $P$. Consequently - as highlighted in the introduction - although a definition of ‘dryness’ through $P - E$ holds over the oceans (to the extent that ocean areas can be considered as being "dry"), it is questionable in a land-based hydrological framework. We note that accumulated changes in soil moisture storage are also relevant, although, the year-to-year changes are negligible in comparison to $P$, $E$ and $Q$. Indeed, if mean soil moisture storage is decreased below a threshold at which it constrains plant transpiration, net effects on vegetation and agriculture could be relevant. Correspondingly, long-term changes in soil moisture storage have also been considered in previous studies (Wang, 2005; Orlowsky and Seneviratne, 2011, 2013), as well as in IPCC reports (Meehl et al., 2007; Seneviratne et al., 2012), although we only focus on fluxes in the present study. It was further found by e.g. Boening et al. (2012) that year to year changes in local water storage in the context of sea level rise can be significant, which locally might influences the computation of 20-year climatologies.

Any change in water availability could have major impacts on agriculture, logistics, power production and various other socio-economic sectors. Figure 3.2 displays mean ensemble changes in $P - E$ comparing the 1980-1999 and the 2080-2099 time periods. Significance at the 95%-level is assigned by
3.3. TRENDS IN P-E

Figure 3.2: Changes in $P - E$ comparing present-day (1980-2000) and future climate (2080-2100) following the RCP8.5 pathway for a) ocean-only and b) land-only areas. Stippling denotes regions where the change is significant at the 95%-level.

computing the Mahalanobis distance using the covariance matrix between the ensemble data cloud within the ($P, E$)-space and the identity line (indicating the line of no change). This methodology accounts for both the uncertainty in $P$ and $E$ simultaneously. Further details are provided in G14.

Over ocean surfaces, the total area experiencing robust changes in $P - E$ comprises 38.7% of all ocean area, with a significant change towards less $P - E$ in ca. 20.7% of all ocean area vs. 18.0% with significant increase in $P - E$ (see Figure 3.2). Thus, a significant surplus in $P - E$ in some regions is basically balanced by a decline in other areas. Significant decreases in $P - E$ (indicating suppressed freshwater fluxes) are basically found in all subtropical ocean basins. A significant increase in $P - E$ (indicating enhanced freshwater fluxes) are found in midlatitude to Arctic ocean regions, whereas positive trends primarily found in the equatorial Pacific Ocean are just partly significant. Signals in the equatorial Atlantic and Indian Ocean are smaller and not significant. Overall, these results basically support the findings of Held and Soden (2006) obtained for zonally averaged estimates, but also support the results of Roderick et al. (2014), stating that the DDWW does not necessarily holds at local (gridbox) scales. These tendencies (for projected changes) are
further consistent with the findings of Durack et al. (2012) for historical changes, which showed increases in salinity for subtropical and decreases in salinity for equatorial and midlatitude ocean areas (which can be summarized as ‘fresh gets fresher and salty gets saltier’).

Over land surfaces, changes in $P - E$ are found to be significant for 22.8% of all land area. In summary, the results with respect to changes in $P - E$ show barely any significant drying signal over land with a significant change towards drier conditions in only 3.3% of all land area. These minor drying regions are mainly located in the Mediterranean and parts of Patagonia, which however, are located close to ocean areas exhibiting strong decreases in $P - E$. On the contrary, significant wetting signals are found for 19.5% of all land area, located entirely in the high latitudes. It is further important to note that no regions with robust signals are located in the tropics.

### 3.4 Aridity changes

The $P - E$ metric alone is insufficient to assess changes towards drying which are not reflected within the water balance, since the limitation of $E$ through soil water is not taken into account (Held and Soden, 2006, G14). To incorporate the specific hydroclimatological characteristics of the land surface into the analysis, the aridity index provides a more meaningful measure of dryness. The aridity index is usually defined as the ratio of $P$ and $E_p$ - here, $R_n/\lambda$ - (Budyko, 1974), and thus conceptually represents the complex interplay of water supply and demand.

Analysing changes in $R_n$ and $P - R_n/\lambda$ (following the same method as applied to $P - E$) provides estimates of changes in aridity shown in Figure 3.3. Since $R_n/\lambda$ is increasing globally due to stronger longwave emissions from the warmer and generally moister atmosphere (Stephens and Ellis, 2008; Allan, 2009; Roderick et al., 2014), a significant shift towards more humid conditions is experienced in regions with a stronger increase in $P$, being the case for only 6.7% of all land area and primarily located in the northern high latitudes. On the contrary, regions with a change in $R_n/\lambda$ exceeding the change in $P$, thus leading to a significant change towards more arid conditions are found for 16.4% of all land area. These changes are basically found in central North America, Central America, Amazonia, southern and northern Africa, southern Europe, the Middle East and central Asia, as well as southern Australia, from which some are potentially related to a poleward expansion of model subtropical dry zones (Scheff and Frierson, 2012; Alessandri et al., 2014). In summary, for a total of 23.1% of all land area a significant shift with respect to the model ensemble spread (either towards more arid or humid conditions) in aridity is projected.

An analysis of aridity changes based on $E_p$ estimated via the Priestley-Taylor method reveals a similar picture; however a much larger fraction of
land area shows significant changes (45.4%). Especially regions experiencing changes towards more aridity are larger and extend even further into adjacent transitional and humid areas (more information is provided in Appendix B).

Figure 3.3: Aridity changes within the 21st century. a) Changes in $P - R_n/\lambda$ comparing present-day (1980-2000) and future climate (2080-2100) following the RCP8.5 pathway and b) changes in $R_n/\lambda$. Stippling denotes regions where the change is significant at the 95%-level.

3.5  Future DDWW: Summary and conclusions

Combining both metrics in a merged framework as introduced in G14 provides a new perspective on changes in hydroclimatological conditions for the land surface. Within the framework we are able to establish that drying or wetting hydroclimatological conditions, either due to changing water availability or atmospheric demand, are significant for ca. 30.6% of all land area. However, it is important to note that significance is assigned with respect to the model ensemble spread and not with respect to internal variability, which might lead to an overestimation of the actual area with change (see e.g. Power et al., 2011). The spatial distribution of trends summarizing the results shown in Fig. 3.2 and 3.3 is illustrated in Fig. 3.4a. Changes in wa-
ter availability are found to be significant mainly in high and mid latitudes, whereas changes in the atmospheric demand are significant in subtropical regions. Thus, a shift towards wetter conditions in the high latitudes is primarily due to \( P \) increasing faster than \( E \) (and partly also faster than \( R_n/\lambda \)). A shift towards drier conditions in subtropical regions is induced by an increase in \( R_n/\lambda \) vs. a decrease (or a weaker increase) in \( P \). Close to the Mediterranean Sea this also results in a significant decrease in \( E \) (not shown).

Contrary to \( P - E \), the aridity index also provides a reliable estimate of the distribution of arid/humid areas (see Fig. 3.4b). Regions with significant \( R_n/\lambda P > 2 \ (R_n/\lambda P < 2) \) are classified as arid (humid) (Middleton et al., 1997). Regions with no significant classification are defined as transitional. The methodology to assign significance is analogous to the method applied above and explained in more detail in G14. The obtained world map (see Fig. 3.4b) is further in good correspondence to the Köppen-Geiger climate classification (Peel et al., 2007). We note that the spatial distribution of arid/humid areas is strongly sensitive to the threshold used to define these areas (see supplementary information).

Determining recent (1980-2000) aridity conditions (displayed in Fig. 3.4b) allows us to compare end of 20th century conditions with projected dryness changes until the end of the 21st century (displayed in Fig. 3.4a), and thus to evaluate the DDWW as shown in 3.4c.

We identify that the paradigm is confirmed for humid areas projected to experience a significant increase in water availability in the high latitudes. Further, the combination of decreasing \( P \) and increasing atmospheric demand \( R_n/\lambda \) leading to a significant increase in aridity in many subtropical areas confirms the paradigm for dry desert regions in Africa and western Asia.

However, the DDWW paradigm is invalidated for the relative large fraction of affected neighboring areas which are currently in a humid or transitional climate regime. These areas include large parts of southern and central Europe and parts southern Africa and North America. Drying conditions are further found in parts of humid tropical Amazonia. Changes towards more arid conditions (despite not being significant regarding the applied test metric) are also found in humid tropical Africa, Indonesia and coastal regions of South America.

Thus, despite the above-mentioned notable exceptions in large areas of the high latitudes and subtropics, we conclude that the ‘dry gets drier, wet gets wetter’ paradigm is generally not confirmed for projected changes in most land areas, because of (i) a lack of robustness of the projected changes in some regions (tropics) and (ii) because many humid to transitional regions are projected to shift towards drier conditions, i.e. not following the paradigm.

In summary we found that uncertainties regarding projected changes in water availability and aridity are large and do not permit reliable predic-
3.5. FUTURE DDWW: SUMMARY AND CONCLUSIONS

Figure 3.4: Investigating the DDWW paradigm. a) Significant drying/wetting trends computed at the grid box level. Dark red (dark blue) denotes a significant change towards drier (wetter) conditions both regarding the land water balance and hydrological regime shifts. Red/orange shows a shift towards more arid conditions. Drying due to changes in the land water balance only is depicted by green/pink color. b) Distribution of arid (orange) to humid (blue) areas within the period from 1980-2000. Beige colors denote transitional areas where no significant attribution is possible. c) Comparing the changes in a) with the hydrological conditions in b) yields an evaluation of the ‘dry gets drier, wet gets wetter’ paradigm. Red/dark blue colors indicate regions where the paradigm is found to be valid. Humid areas getting drier (orange) are widely found. d) Conceptual evaluation of the DDWW, with areas confirming (dark grey) and invalidating (black) the paradigm compared to areas showing no robust trend. Note that Antarctica is not accounted for in the subplots.

Robust signals showing an increase in water availability are found for high-latitude regions of the northern hemisphere. Significant increases in aridity are found for some subtropical regions (such as e.g. the Mediterranean region), but also in adjacent humid regions, supporting previous findings of dryland expansion (Feng and Fu, 2013; Chou et al., 2013; Cook et al., 2014; Alessandri et al., 2014) and dynamically-induced poleward expansion of subtropical dry zones (Cherchi et al., 2010; Scheff and Frierson, 2012; Allan, 2014; Alessandri et al., 2014).

Based on these results the DDWW is confirmed for only ca. 19.5% of all land area in climate projections, whereas the DDWW is invalidated for another ca. 11.1%. Hence we do not find substantial support for the DDWW paradigm in projections.
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Part II

Limitations and expansion of the Budyko framework
Introducing a probabilistic Budyko framework

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**Abstract** Water availability is of importance for a wide range of ecological, climatological and socio-economic applications. Over land, the partitioning of precipitation into evapotranspiration and runoff essentially determines the availability of water. At mean annual catchment scales, the widely used Budyko framework provides a simple, deterministic, first order relationship to estimate this partitioning as a function of the prevailing climatic conditions. Here we extend the framework by introducing a method to specify probabilistic estimates of water availability that account for the nonlinearity of the underlying phase space. The new framework allows to evaluate the predictability of water availability that is related to varying catchment characteristics and conditional on the underlying climatic conditions. Corresponding results support the practical experience of low predictability of

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CHAPTER 4. PROBABILISTIC BUDYKO FRAMEWORK

4.1 Introduction

Assessing continental water availability is essential for a wide range of applications (Milly et al., 2005; Rockström et al., 2009; Immerzeel et al., 2010; Gerten et al., 2011; Seager et al., 2013; Orlowsky et al., 2014) and is substantially determined by the partitioning of precipitation (P) into evapotranspiration (E) and runoff (Q). However, these hydrological variables are subject to large uncertainties both in observations and model estimates (Seneviratne et al., 2010; Gudmundsson et al., 2011, 2012; Mueller et al., 2013; Greve et al., 2014). Furthermore, contemporary land surface models are computationally demanding and require vast sets of input parameters. Thus simpler approaches to estimate the surface water balance are receiving regular attention (Koster and Milly, 1997; Kirchner, 2009; Koster and P. Mahanama, 2012; Orth et al., 2013). In this context, a simple, first-order relationship to quantify the partitioning of \( P \) into \( E \) and \( Q \) at mean annual catchment scales as a function of climatic conditions, developed by Budyko (1974), has experienced a revival in recent years (Milly, 1994; Koster and Suarez, 1999; Zhang et al., 2001, 2004; Potter et al., 2005; Donohue et al., 2007; Yang et al., 2008; Roderick and Farquhar, 2011; Gentine et al., 2012; Williams et al., 2012; Li et al., 2013; Xu et al., 2013; Destouni et al., 2013; Berghuijs et al., 2014; Greve et al., 2014). Within the Budyko framework, climatic conditions are expressed in terms of the aridity index, being the dimensionless ratio of potential evaporation \( E_p \) divided by \( P \). The corresponding relationship is nonlinear and constrained to physical limits, namely the atmospheric water demand (\( E < E_p \)) and the atmospheric water supply (\( E < P \)) limit (see Figure 4.1). The framework serves as a powerful tool used to e.g. assess changes in catchment water balance as a function of climate change (Roderick and Farquhar, 2011; Renner et al., 2012; Renner and Bernhofer, 2012; van der Velde et al., 2013), to predict water availability in ungauged basins (Blöschl et al., 2013; Li et al., 2013; Xu et al., 2013), or to evaluate hydrological datasets (Greve et al., 2014).

The original curve derived by Budyko (1974) is entirely deterministic and non-parametric. However, he acknowledged that variations around the curve can arise depending on local conditions. Later assessments did indeed find widespread evidence for systematic variations related to various catchment and climate characteristics, such as e.g. vegetation (Zhang et al., 2001; Donohue et al., 2007; Williams et al., 2012; Li et al., 2013), soil properties (Porporato et al., 2004; Donohue et al., 2012), seasonality characteristics (Milly, 1994; Potter et al., 2005; Gentine et al., 2012; Chen et al., 2013; Berghuijs et al., 2014), groundwater (Istanbulluoglu et al., 2012), and topographic controls (Shao et al., 2012; Xu et al., 2013). Several studies also suggest hybrids...
4.1. INTRODUCTION

Figure 4.1: The traditional Budyko Curve (corresponding to $\omega = 2.6$ in Fu’s equation (Fu, 1981; Zhang et al., 2004), solid gray) enclosed by the $\omega = 2.6 +/− 1$ curves (dashed gray). The Euclidean distance between the curves is different for different values of $E_p/P$.

of various controls (Milly, 1994; Gentine et al., 2012; Donohue et al., 2012; Xu et al., 2013). However, so far the combination of previous findings is not conclusive.

Further, many subsequently derived formulations of the Budyko curve are parametric including one or more free parameters (Fu, 1981; Choudhury, 1999; Zhang et al., 2001, 2004; Porporato et al., 2004; Yang et al., 2008; Gerrits et al., 2009; Wang and Tang, 2014). The model of Porporato et al. (2004) further assumes that $P$ is distributed, making it a stochastic model. In this study we make use of the popular one-parameter relationship being analytically derived from basic phenomenological assumptions by Fu (1981) and Zhang et al. (2004). Fu’s equation spans the underlying Budyko space enclosed by the demand and supply limit and is expressed as follows

$$\frac{E}{P} = 1 + \frac{E_p}{P} - \left(1 + \left(\frac{E_p}{P}\right)^{\omega}\right)^{\frac{1}{\omega}}. \quad (4.1)$$

The free parameter $\omega$ in Fu’s equation has no a priori physical meaning, but is usually interpreted as an integrative property of all catchment and climatic characteristics (e.g. seasonal cycle) other than the prevailing mean climatic conditions (expressed in terms of $E_p/P$), including vegetation, geographical, topographical and soil properties. Although no direct estimation of $\omega$ is possible for ungauged catchments, Zhang et al. (2004) proposed that $\omega$ is larger for forested than for grassland catchments, i.e. $E$ tends to be larger in the former for the same amount of precipitation. We note, however, that recent results suggest a possible different dependence of ET on land cover, with higher ET over grassland (Teuling et al., 2010; Williams et al.,
Shao et al. (2012) identified four factors being of major importance for the determination of $\omega$, including e.g. the phase difference in the seasonal cycles of $P$ and $E_p$ (related to Milly (1994)). Li et al. (2013) attempted to relate $\omega$ to Normalized Density Vegetation Index (NDVI) measurements and proposed a linear relationship for large catchments, whereas no relationship is found for small to medium-sized catchments. Yang et al. (2009) found that the influence of vegetation on the Budyko curve is different under different climate conditions. In a more comprehensive approach, Xu et al. (2013) used a neural network model to assess the influence of vegetation, landscape characteristics, and geolocation influences on $\omega$. However, apart from its universal integrative nature no definite conclusions about the process controls of $\omega$ have been reached up to now.

4.2 Motivation

Many previous studies assess physical controls of variations within the Budyko framework, but make no statement about the nonlinearity of the phase space and the corresponding problematic use of Euclidean distance measures. Apparently, small variations of $\omega$ in very wet regimes (small aridity index) being narrowly bounded by the demand limit are potentially different from same-sized variations of $\omega$ in drier regimes (see Fig. 4.1). In this study we therefore account for the nonlinearity of the underlying Budyko space by establishing a probabilistic Budyko framework based on Fu’s Equation. The new framework allows the derivation of distribution estimates rather than having only a single value of $E/P$ at a given aridity index and allows to quantify deviations from the mean curve in a probabilistic sense.

4.3 A probabilistic Budyko framework

4.3.1 Theory

To establish a probabilistic representation of the Budyko framework, we use Fu’s equation (Equation 4.1), since it is based on fundamental assumptions only (Fu, 1981; Zhang et al., 2004). The parameter $\omega$ in Equation 4.1 is a mathematical parameter being a necessary result of the solution within the Budyko space and has no a priori physical meaning. By definition $\omega \in ]1, \infty]$ and every point within the limits of the Budyko space could be assigned to a specific $\omega$. It is, however, important to note that under real world conditions the infimum of the set of values for $\omega$ is not necessarily 1, but could be larger (Zhang et al., 2004; Wang and Tang, 2014).

The large scatter of observations around the original Budyko curve (Budyko, 1974) shown in previous assessments strongly indicates that $\omega$ is not a constant and differs between catchments. However, since no definite
4.3. A PROBABILISTIC BUDYKO FRAMEWORK

primary control of \( \omega \) was identified to the present, we hypothesize that the integrative combination of all catchment and climate characteristics (except the prevailing aridity index) into \( \omega \) can be characterized as a stochastic process. Therefore, we assume that \( \omega \) follows a certain (initially unknown) distribution: \( \omega \sim D(p) \) with \( D \) being an arbitrary distribution low bounded to 1 (since \( \omega \in ]1, \infty[ \)) and \( p \) the corresponding set of distribution parameters.

4.3.2 The Budyko distribution

Given the theoretical background, we are able to obtain a distribution of \( E/P \) for a given \( E_p/P \) which depends on the distribution parameters of the underlying distribution \( D(p) \) of \( \omega \) only. \( D \) could be of any form being low bounded to 1.

Numerical simulation

Since an analytical solution for the probability density function (pdf) of \( E/P \) is not feasible, the problem is solved by stochastic simulation (following a Monte Carlo approach). For a large number of simulations, \( n \) random variables \( y_n = (E/P)_n \) are generated from Equation 4.1 for a given \( x = E_p/P \) by assuming \( \omega \sim D(p) \). Distributional properties (mean values, moments, quantiles, etc.) of the obtained Budyko distribution are either estimated from the simulated distribution directly or from the kernel density estimate (if the number of simulations \( n \) is small and thus does not permit a direct estimation of properties).

General characteristics

To illustrate the general characteristics of the Budyko distribution we define a set of four arbitrary example distributions of \( \omega \) (see Fig. 4.2). These are (i) a truncated normal distribution (low bounded to 1), (ii) a uniform distribution, and (iii) two different gamma distributions (in the form \( 1 + \Gamma(k, \theta) \), with \( k \) and \( \theta \) being the respective shape and scale parameters). Three distributions (subfigures 4.2a, b, c) share a common median of \( \omega \approx 2.6 \), representing the original Budyko curve, whereas subfigure 4.2d represents a smaller median \( \omega \) (thereby highlighting that the probabilistic framework is not constrained to the original Budyko curve and that a median change of the \( \omega \)-distribution also affects higher central moments of the resulting Budyko distribution). The complexity of the estimated Budyko distribution highlights the nonlinearity of the Budyko space and the need to establish a probabilistic framework rather than the deterministic original approach. The dispersion of the Budyko distribution is conditional on the aridity index and its value strongly depends on the distributional choice. However, the basic characteristics with rather low dispersion measures under very wet conditions and somewhat
Figure 4.2: The probabilistic Budyko framework with $\omega$ following a) a truncated normal distribution, b) an uniform distribution and c) and d) two different gamma distributions. The distributions in a), b) and c) share a common median $\omega = 2.6$, which corresponds to the traditional Budyko curve (solid black line). The respective quantiles are shaded, with the 25th/75th quantile (thick dashed line) and 10th/90th quantile (thin dashed line) highlighted.

higher dispersion measures under transitional conditions ($E_p/P \approx 1$) is universal for unimodal distributions of $\omega$.

Figure 4.2 further illustrates new possibilities to determine statistical distance measures to the median curve, to identify ‘extreme’ catchments and to compare departures from the median curve under different climatic conditions in a probabilistic perspective. This has implications for (1) assessing the heavily debated influence of various land surface characteristics on water resources and associated feedbacks to the atmosphere (Pitman et al., 2009; Teuling et al., 2010; de Noblet-Ducoudré et al., 2012; Williams et al., 2012; Davin et al., 2014), (2) robust significance testing, (3) climate change assessments carried out within the Budyko framework, and (4) dataset and model validation.

4.4 Applications

4.4.1 Observational data

Here we show an example application of the new framework using a distribution estimate of $\omega$ based on high quality observational data.

We use data from the MOdel Parameter estimation EXperiment (MOPEX) (Schaake et al., 2006) to estimate the distribution properties of $\omega$. The dataset provides quality-controlled daily estimates of $P$ and $Q$, as well as
climatological $E_p$ (based on pan evaporation), for 438 catchments distributed across the United States spanning the time period from 1949 to 2003, and it was used in recent studies related to the Budyko framework (Renner and Bernhofer, 2012; Gentile et al., 2012; Xu et al., 2013; Berghuijs et al., 2014). We use a subset of $N = 411$ catchments (see Figure 4.3a) with continuous time series between 1974-2003 and compute the corresponding 30-year $P$, $E_p$ and $P - Q = E$ averages.

### 4.4.2 A Budyko distribution for the United States

The catchment specific $\omega_n$ is estimated numerically for every catchment $n \in 1, 2, ..., N$ following a previously published approach (Zhang et al., 2004; Li et al., 2013). Evaluating the empirical distribution of $\omega_n$ for the MOPEX catchments reveals that it is (i) low-bounded by 1 (following the definition of $\omega$) and (ii) right-skewed (see Figure 4.3b). Based on this visual inspection, we assume that the $\omega_n$-values approximately follow a right skewed gamma distribution low-bounded by 1 ($\omega \sim 1 + \Gamma(k, \theta)$) with shape $k \approx 4.54 \pm 0.45$ and scale $\theta \approx 0.37 \pm 0.038$ (see Figure 4.3b). The distribution parameters $(k, \theta)$ are estimated with a maximum likelihood approach. The standard deviations (estimated via bootstrapping 1000 replications from which a random subset is also depicted in Figure 4.3b) provide a range of uncertainty which however do not suggest major changes on the basic characteristics of the estimated gamma distribution. Please note that the actual standard deviation of the bootstrapped median estimates of $\omega$ is ca. 0.036 and thus much smaller than the range of uncertainty for the parameters $(k, \theta)$ potentially suggests. This is mainly due to uncertainty propagation related to the fact that the bootstrapped estimates of $(k, \theta)$ are highly correlated ($p_{k, \theta} = -0.96$). The overall median curve ($\omega = 2.56$) is very close to the original Budyko curve ($\omega = 2.6$). However, using a gamma distribution is somewhat arbitrary and only motivated by the shape of the empirical distribution of $\omega$. Other distributional choices are potentially suitable as well. To further justify our approach, we have performed a cross-validation by randomly choosing 10,000 training samples from the set of MOPEX catchments. Each of the training samples contains 90% of the data and is used to estimate the parameters of a gamma distribution representing the distribution of $\omega$ using a maximum likelihood estimator. Validation against the empirical distribution of $\omega$ for the residual 10% of catchments is performed using both the Anderson-Darling (AD) and the Cramer-von Mises (CvM) goodness-of-fit test metric. The percentage of samples for which the parametrized gamma distribution cannot be ruled out to represent the empirical distribution of the remaining catchments at a 95% significance level is for AD: 92.5% and for CvM: 93.5%, providing strong evidence on the validity of the assumption that $\omega$ likely follows a gamma distribution. Further, since $\omega$ itself is by definition independent from the aridity index, the estimated distribution of $\omega$ could be assumed to be...
Figure 4.3: (a) The set of 411 MOPEX catchments with their respective $\omega$-value. (b) The histogram of all $\omega$-values (grey bars) shown alongside the fitted gamma distribution (black line) and a random subset of 30 bootstrapped distributions (brown lines). c) The probabilistic Budyko framework estimated from the set of 411 MOPEX catchments. The estimated gamma distribution (see Figure 4.2) is used to compute the Budyko distribution and the conditional pdfs at $E_p/P = 0.5, 1.5, 2.5, 3.5$ (bottom plots, with the solid horizontal line indicating the physical limits and the dashed line the original Budyko value). The data cloud of the MOPEX catchments is indicated by grey dots.
valid for all climatic conditions. The obtained Budyko distribution is shown in Figure 4.3c alongside the underlying data cloud of the MOPEX catchments (gray dots). Also shown are the conditional pdfs at selected values of $\frac{E_p}{P}$, highlighting differences in the distribution of $E/P$ as a function of the mean climatic conditions.

### 4.4.3 Predictability of water availability

The dispersion of the obtained Budyko distribution conditional on the aridity index is an indication of how strongly predictions of water availability are controlled by $\omega$ (and hence e.g. land parameters or seasonality).

The interquartile range (IQR), being a robust measure of dispersion, is shown in Figure 4.4a as a function of $\frac{E_p}{P}$. The corresponding curve reveals rather low values under very wet conditions (small $\frac{E_p}{P}$). IQR is increasing initially with increasing $\frac{E_p}{P}$ and reaches its maximum value at $\frac{E_p}{P} \approx 1.4$. Under dry conditions IQR remains at a relatively high level but is slowly decreasing with increasing dryness.

The obtained IQR curve provides an estimate of the uncertainty due to varying catchment characteristics which affect the prediction of $E/P$ or water availability, respectively. The uncertainty itself is conditional on the climatic (boundary) conditions. It follows from Figure 4.4a that the uncertainty is largest in transitional climate regions, indicating lower predictability of water availability compared to either wet or dry regions. The IQR curve is further used to quantify the uncertainty dependent on climatic conditions underlying the predictions of mean annual water availability for each MOPEX catchment (see Figure 4.4b). High uncertainty and thus low predictability is found for many catchments in the Midwest and the Rocky Mountains. Predictability is somewhat better for southeastern and northeastern catchments, including some mountainous Appalachian catchments. Wet catchments in the far Northwest reveal highest predictability.

Applying the same methodology globally by using gridded $P$ and $E_p$ estimates provides a map of predictability at gridscale (Figure 4.4c). We use here an $E_p$ dataset (Sheffield et al., 2006, 2012) based on the Penman-Monteith method (Monteith, 1965) and Global Precipitation Climatology Project (GPCP) precipitation estimates (Adler et al., 2003). While the absolute values of IQR rely on the distributional estimate derived from the set of MOPEX catchments, the basic pattern of low and high predictability is in itself generally unrelated to the choice of any likewise unimodal distribution, enabling us to make qualitative statements for regions outside the set of MOPEX catchments. However, it is important to note that the distribution of $\omega$ could basically follow any kind of distribution that is low bounded to 1, but previous findings using larger sets of catchments covering also other regions of the world indicate similar unimodal distributional properties as derived from the MOPEX catchments (Xu et al., 2013). Since the MOPEX
Figure 4.4: Predictability of water availability. (a) The interquartile range of $E/P$ estimated from the Budyko distributions shown in Figure 4.3 and conditional on the aridity index. (b) The interquartile range conditional on the respective aridity index for each MOPEX catchment underlayed by the (c) interquartile range conditional on the aridity index estimated from gridded $P$ and $E_p$ datasets.
4.5. SUMMARY AND CONCLUSIONS

dataset also covers a broad range of climatic conditions and its median corresponds very well to the established original Budyko curve ($\omega = 2.6$), we use it as a surrogate for global assessments (see Fig. 4.4c). Based on this assumption, highest predictability is found in either very dry (desert regions) or very wet/cold climates (very high latitudes of Asia/Europe), but also in Central Europe, in the Northeast of North America, parts of East Asia. Predictability is lowest in many parts of the subtropics and tropics, but also in some subpolar regions encompassing northern Canada and Siberia. The results are consistent with the common observed low predictability of runoff in transitional climates (Parajka et al., 2013; Salinas et al., 2013; Blöschl et al., 2013). We also note that high hydrological uncertainties previously found for some regions (like e.g. Amazonia, Mueller et al. (2011)) are probably due to uncertainties in the atmospheric forcing variables (being related to $E_p/P$), whereas our approach identifies uncertainties stemming from all catchment-specific variables other than $E_p/P$.

4.5 Summary and conclusions

We establish here a new probabilistic Budyko framework based on the analytically derived Fu equation (Fu, 1981; Zhang et al., 2004). The obtained framework accounts for systematic variations from the originally deterministic curve and the nonlinearity of the underlying Budyko space. The probabilistic framework enables us to derive Budyko distributions using observational data and to theoretically assess the uncertainty stemming from varying land surface and catchment characteristics affecting the prediction of water availability. This uncertainty is itself conditional on climatic conditions and largest in transitional climate regions. Especially in these regions it is thus essential to consider variations in land surface characteristics and other catchment specific properties for the prediction of water resources. Further, the low predictability of water availability in regions being exposed to severe water scarcity under climate change (like e.g. in the Mediterranean, Orlowsky and Seneviratne (2013)) has major implications for the prediction of long term changes in water resources.

The new framework further provides additional perspectives on the common practice of assessing variations in the Budyko space using euclidean techniques (Zhang et al., 2001, 2004; Gerrits et al., 2009; Williams et al., 2012; Gentine et al., 2012; Greve et al., 2014). In this context, the probabilistic framework could also provide new insights on secondary controls (land cover, topography, etc.) of the land water balance.

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The Budyko framework beyond stationarity


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Abstract Water availability is of major importance for a wide range of socio-economic sectors. Over land, the partitioning of precipitation (\(P\)) into evapotranspiration (\(E\)) and runoff (\(Q\)) is the key process to assess hydrological conditions. For climatological averages, the Budyko framework provides a simple first order relationship to estimate the evaporative index \(E/P\) as a function of the aridity index \((E_p/P\), with \(E_p\) denoting potential evaporation). However, a major downside of the Budyko framework is its limitation to steady state conditions, being a result of the assumption of a closed land water balance. Nonstationary processes coming into play at other than mean annual catchment scales are thus not represented. Here we propose an analytically derived new formulation of the Budyko curve including an additional

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parameter being implicitly related to the nonlinear storage term of the land water balance. The new framework is comprehensively analysed, showing that the additional parameter leads to an upward rotation of the original supply limit and therefore implicitly represents the amount of additional water available for evaporation. The obtained model is further validated using standard datasets of $P$, $E$ and $E_p$. It is shown that the model is capable to represent first-order seasonal dynamics within the hydroclimatological system.

5.1 Introduction

The Budyko framework serves as a tool to predict mean annual water availability as a function of aridity. It is widely-used and well-established within the hydrological community, both due to its simplicity and long history, combining experience from over a century of hydrological research. Since Budyko (1956, 1974) derived a formulation of the curve based on findings of Schreiber (1904) and Ol’Dekop (1911), several other formulations have been postulated, which however are numerically surprisingly similar (Schreiber, 1904; Ol’Dekop, 1911; Turc, 1955; Mezentsev, 1955; Pike, 1964; Fu, 1981; Choudhury, 1999; Zhang et al., 2001, 2004; Porporato et al., 2004; Yang et al., 2008; Donohue et al., 2012; Wang and Tang, 2014; Zhou et al., 2015b). Many of these formulations are empirically derived and only few are analytically determined from simple phenomenological assumptions (Fu, 1981; Milly, 1994; Porporato et al., 2004; Zhang et al., 2004; Yang et al., 2007). Nonetheless, derived functional forms in all formulations are deterministic and assessments on controls determining the observed systematic scatter around the mean Budyko curve have been subject to numerous studies. A variety of catchment and climate characteristics, such as e.g. vegetation (Zhang et al., 2001; Donohue et al., 2007; Williams et al., 2012; Li et al., 2013; Zhou et al., 2015a), seasonality characteristics (Milly, 1994; Potter et al., 2005; Gentine et al., 2012; Chen et al., 2013; Berghuijs et al., 2014), soil properties (Porporato et al., 2004; Shao et al., 2012; Donohue et al., 2012), and topographic controls (Shao et al., 2012; Xu et al., 2013) have been proposed to exert a certain influence on the scatter within the Budyko space. Also complex hybrids of various controls (Milly, 1994; Gentine et al., 2012; Donohue et al., 2012; Xu et al., 2013) have been considered, but until present, no conclusive statement on controls were made.

In this study we make use of the formulation derived by Fu (1981) and Zhang et al. (2004). They derive the following functional form between $E/P$ and $\Phi = E_p/P$ analytically from simple physical assumptions:

$$\frac{E}{P} = 1 + \Phi - (1 + (\Phi)^{\omega})^{\frac{1}{\omega}}, \quad (5.1)$$

where $\omega$ is a free model parameter ($\omega = 2.6$ results in the original Budyko
curve). The obtained curve is subject to two physical constraints constituting both the water demand and supply limit. The water demand limit represents $E$ being limited by $E_p$, whereas the water supply limit determines $E$ to be limited by $P$ (see Fig. 5.1). Hence, the supply limit requires steady-state conditions. The storage term ($dS/dt$) in the land water balance equation

$$\frac{dS}{dt} = P - E - Q \tag{5.2}$$

is consequently neglected, a generally valid approach at mean annual catchment scales. Although we note, that year to year changes in soil moisture may happen, e.g. under transient climate change (Wang, 2005; Orlowsky and Seneviratne, 2013). However, the assumption of steady-state conditions does not permit the usage of the Budyko framework at monthly to seasonal time scales and constitutes a major limitation of the framework. Only few assessments addressed this limitation. Potter and Zhang (2007) derived a formulation based on previous work by Milly (1993) in order to model interstorm $E$. In a comprehensive top-down approach, Zhang et al. (2008) developed a water balance model for subannual to mean annual time scale. They suggested that model complexity has to increase at intrannual time scales to account for soil-moisture dynamics, and they extended the Budyko model accordingly by introducing four additional parameters. Chen et al. (2013) extended the Budyko model to seasonal time scales by introducing a seasonal aridity index that accounts for storage changes. Although these approaches provide interesting insights on the Budyko hypothesis at subannual time scales, they are still derived empirically. Nevertheless, all approaches agree on the necessity to include storage changes, but so far a robust, theoretical incorporation into the Budyko framework is missing.

In this work, we aim to analytically derive a new Budyko formulation for dynamic conditions at e.g. subannual time scales. Our approach is based on simple phenomenological assumptions in which the storage term is implicitly considered. This is achieved by reformulating the set of differential equations given in Fu (1981) and Zhang et al. (2004) such that the water supply limit is no rigid physical constraint.

5.2 Deriving a new formulation

5.2.1 Preliminary Assumptions

On the basis of Fu (1981) and Zhang et al. (2004), we postulate that for a given potential evaporation, the rate of change in evapotranspiration as a function of precipitation ($\partial E/\partial P$) increases with residual potential evaporation ($E_p - E$) and decreases with precipitation. Similar assumptions are made regarding the rate of change in evapotranspiration as a function of po-
CHAPTER 5. NONSTATIONARY BUDYKO FRAMEWORK

Figure 5.1: The original Budyko curve (red), limited by both the demand limit \((E = E_p)\) and the supply limit \((E = P)\).

Potential evaporation \((\partial E/\partial E_p)\) by considering residual precipitation \((P - E)\). Hence, both ratios can be written as

\[
\frac{\partial E}{\partial P} = f(x) \quad (5.3a)
\]

\[
\frac{\partial E}{\partial E_p} = g(y) \quad (5.3b)
\]

with

\[
x = \frac{E_p - E}{P} \quad (5.4a)
\]

\[
y = \frac{P - E}{E_p} \quad (5.4b)
\]

Considering \(E_p\) being a natural constraint of \(E\), it follows

\[
\frac{\partial E}{\partial P} \bigg|_{x=0} = 0 \quad (5.5)
\]

The original approach of Fu (1981) further assumes that \(P\) is a natural constraint of \(E\), giving the following boundary condition
5.3. CHARACTERISTICS OF THE NEW FRAMEWORK

\[
\frac{\partial E}{\partial E_p} \bigg|_{y=0} = 0. 
\] (5.6)

This assumption requires steady-state conditions and is consequently valid at mean annual catchment scales (such that \(P - E \geq 0\)) only. However, due to storage changes, on shorter time scales and smaller spatial scales \(E \geq P\) (respectively, \(y \leq 0\)) is possible. In this case \(E_p\) remains the only constraint of \(E\). The minimum value \(y_{\text{min}}\) of \(y\) thus lies within the interval between \(-1\) and \(0\) and depends on the additional amount of water being available for evaporation (and thus implicitly refers to the storage term in equation 5.2). For convenience we define \(y_0 = -y_{\text{min}}\) (and thus \(y_0 \in [0, 1]\)). The boundary condition 5.6 is then redefined as

\[
\frac{\partial E}{\partial E_p} \bigg|_{-y_0} = 0. 
\] (5.7)

5.2.2 Solution

Solving the system of the differential equations 5.3a,b using boundary condition 5.5 and the new condition 5.7 yields the following solution (details are provided in Appendix A):

\[
E = E_p + P - ((1 - y_0)^{\kappa-1}E_p^\kappa + P^\kappa)\frac{1}{\kappa} 
\] (5.8)

with \(\kappa\) being a free model parameters. It follows

\[
\frac{E}{P} = F(\Phi, \kappa, y_0) = 1 + \Phi - \left(1 + (1 - y_0)^{\kappa-1} (\Phi)^\kappa\right)^{\frac{1}{\kappa}}. 
\] (5.9)

Similar to the traditional Budyko approach a free model parameter (named \(\kappa\) to avoid confusion with the traditional \(\omega\)) is obtained. The parameter \(y_0\) is directly related to the new boundary condition. Hence, in contrast to \(\kappa\), which is a mathematical constant, \(y_0\) has an actual physical interpretation. However, similarly the \(\omega\) parameter in Fu’s equation, \(\kappa\) is potentially an integrator of all other catchment properties than the aridity index.

5.3 Characteristics of the new framework

The obtained new formulation given in equation 5.9 is similar to equation 5.1, but includes \(y_0\) as a new parameter (Assuming \(\kappa = 2,6\), corresponding to the original Budyko curve with \(\omega = 2.6\) and an example set of \(y_0\)-values, Fig. 5.2 shows a set of curves providing insights on the basic characteristics of the new equation).
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Figure 5.2: Set of curves of the new framework for $\kappa = 2.6$ and different $y_0$. Note that the obtained curve for the parameter set $(\kappa, y_0) = (2.6, 0)$ corresponds to the original Budyko curve ($\omega = 2.6$). The supply limit (dashed black line) is systematically exceeded if $y_0 < 0$ and the demand limit (solid black line) is reached if $y_0 = -1$.

First, if $y_0 = 0$ (being the original boundary condition) the obtained curve corresponds to the steady-state framework of Fu (1981) and Zhang et al. (2004), which is also evident from equation 5.9 and shows that both model formulations are consistently transferable. If $y_0 > 0$, the supply limit is systematically exceeded. The exceedance of the supply limit increases with increasing $y_0$. If further $y_0 = 1$, the demand limit is reached. All curves are continuous and strictly increasing.

Taking a closer look at the underlying boundary conditions and definitions (see section 5.2.1) reveals that $y_0$ implicitly accounts for the amount of additional water (besides water supplied through $P$) available for $E$. Since $y_{\text{min}}$ is explicitly defined to be the minimum of $y = (P - E)/E_p$, the quantity $y_0 = -y_{\text{min}}$ physically represents the maximum fraction of $E$ relative to $E_p$, which is not originating from $P$. A larger fraction consequently results in higher $y_0$-values and thus in a stronger exceedance of the original supply limit. Further details on $y_0$ is provided in section 5.4.

The sensitivity $\partial F(\Phi, \kappa, y_0)/\partial \Phi$ under varying $\kappa$ and for three preselected values of $y_0$ is illustrated in Fig. 5.3. The sensitivity $\partial F(\Phi, \kappa, y_0)/\partial \Phi$ for different values of $y_0$ and $\kappa$ shows the effect of the parameter choice on changes in $E/P$ relative to changes in $\Phi$. In general, the sensitivity is largest for small $\Phi$ (humid conditions), due to the fact that changes in $E/P$ basically follow the demand limit (resulting in a sensitivity close to 1) regardless of parameter set $(\kappa, y_0)$. For different parameter settings, the sensitivity generally decreases with increasing $\Phi$. For small values of $y_0$ (close to zero), sensitiv-
5.4. INTERPRETING THE NEW PARAMETER $y_0$

The new parameter $y_0$ is, in contrast to $\kappa$, physically well defined. The combination of equation 5.4b and 5.7 shows that $y_0$ is implicitly related to the amount of additional water (besides water supplied through $P$), which is available for $E$. If we rewrite equation 5.4b with respect to $y_0$

Figure 5.3: The sensitivity $\partial F/\partial \Phi$ under varying $y_0$, for $\kappa = 2.6$ (left, similar to the original Budyko framework if $y_0 = 0$), $\kappa = 1.6$ (center) and $\kappa = 4$ (right). Blueish colors denote high, reddish colors low sensitivity.

ity becomes smallest with increasing $\Phi$, since small $y_0$ indicates conditions similar to steady-state conditions being constraint by the (horizontal and thus implying zero sensitivity) original supply limit. Further, the smallest sensitivity is reached for large values of $\kappa$. Large values of $y_0$ (close to 1) indicate conditions mainly constrained by the demand limit, thus implying a sensitivity close to 1.

A similar analysis is performed for varying values of $\kappa$ under three pre-selected levels of $y_0$ (see Fig. 5.4). For $y_0 = 0$ (steady-state conditions), the sensitivity $\partial F/\partial \Phi$ is under humid conditions ($\Phi < 1$) rather large, since changes in $E/P$ are mainly constrained by demand limit. This especially applies for large values of $\kappa$. Under more arid conditions ($\Phi > 1$), the Budyko curve slowly converges towards the (horizontal) supply limit, resulting in a near-zero sensitivity. For $y_0 = 0.2$, denoting conditions relatively similar to steady-state conditions, the decrease in sensitivity with increasing $\Phi$ is weaker, whereas for $y_0 = 0.8$, denoting conditions where $E$ is mainly constraint by the demand limit, sensitivity is large for large $\kappa$-values and decreases rather slowly with increasing $\Phi$. 

5.4 Interpreting the new parameter $y_0$
Figure 5.4: The sensitivity \( \partial F / \partial \Phi \) under varying \( \kappa \), for \( y_0 = 0 \) (left), \( y_0 = -0.2 \) (center) and \( y_0 = -0.8 \) (right). Blueish colors denote high, reddish colors low sensitivity.

\[
y_0 = -y_{min} = -\left( \frac{P - E}{E_p} \right)_{min} = -\frac{P_{min} - E_{max}}{E_p}, \quad \text{if} \quad P_{min} - E_{max} < 0, (5.10)
\]

where \( P_{min} \) and \( E_{max} \) are chosen in order to minimize \( y_{min} \) for a given \( E_p \), we obtain a linear equation in terms of aridity index

\[
\left( \frac{E}{P} \right)_{max} = y_0 \left( \frac{E_p}{P_{min}} \right) + 1, (5.11)
\]

which constitutes the mathematical and physical meaning of \( y_0 \) within the new framework. That is, that \( y_0 \) determines the maximum slope of the upper limit, against which the obtained curve from equation 5.9 asymptotically converges to if \( \kappa \to \infty \) (see Fig. 5.5). Physically, \( y_0 \) determines the maximum \( E/P \) that is reached in relation to \( \Phi \) within a certain time period and spatial domain. Technically speaking, \( y_0 \) determines the slope of the upper limit such that all possible pairs \( (\Phi, E/P) \) are just below the line \( y_0 \Phi + 1 \). It is further important to note that for mean annual conditions \( (P - E \geq 0) \), \( y_0 = 0 \) is considered, which results in a zero slope and thus determines the original supply limit of 5.1.

However, the actual slope \( m \) of the upper limit is smaller than \( y_0 \), but directly related to both \( y_0 \) and \( \kappa \) as follows (see Appendix B for more information)

\[
m = 1 - (1 - y_0)^{1 - \frac{1}{\kappa}}. (5.12)
\]

The relative difference between the maximum slope \( y_0 \) and the actual slope \( m \) of the upper limit (being the ratio of \( y_0/m \)) is thus determined following the relationship...
5.4. INTERPRETING THE NEW PARAMETER $Y_0$

Figure 5.5: Difference between the actual ($m$) and maximum slope of the supply limit for different values of $\kappa$ (red: $\kappa = 1.5$, green: $\kappa = 2.6$ and blue: $\kappa = 6$) and $y_0 = -0.3$. The maximum slope ($m = y_0 = -0.3$) is reached if $\kappa \to \infty$.

Figure 5.6: The ratio $-y_0/m$ as a function of both $y_0$ and $\kappa$ estimated from equation 5.13.

$$\frac{y_0}{m} = (1 - y_0)^{1/k}.$$  \hspace{1cm} (5.13)

The ratio $y_0/m$ as a function of both $y_0$ and $\kappa$ is illustrated in Fig. 5.6. For small $\kappa$ and large $y_0$ (close to 1), the difference between the actual slope $m$ and the maximum slope $y_0$ is large, whereas for large $\kappa$ the actual slope $m$ converges towards $y_0$. However, in any case, $y_0$ determines the maximum overshoot allowed with respect to the original supply limit at $y_0 = 0$. 
Taking into account that \( y_0 \) is well-defined by equation 5.10, the parameter is in the following estimated from data. In the following, we use standard datasets of \( P, E \) and \( E_p \) to evaluate the performance of the obtained model described by equation 5.8.

### 5.5 Assessing the framework with observations

The new framework allows to compute \( E \) as a function of both \( P \) and \( E_p \). Here we use well-established estimates of all three variables: Global Precipitation Climatology Project (GPCP) precipitation estimates, an \( E_p \) dataset (Sheffield et al., 2006, 2012) based on the Penman-Monteith method (Monteith, 1965), and the LandFlux-Eval \( E \) estimates (Mueller et al., 2013), for the 1990-2000 time period and bilinearly interpolated to a unified 1°-grid.

We estimate the parameters \( \kappa \) and \( y_0 \) at gridpoint scale by determining \( y_0 \) from data (using equation 5.10) in order to obtain a fixed parameter for the whole time period. After \( y_0 \) is estimated, \( \kappa \) is estimated using a least squares fitting approach. However, estimating \( y_0 \) from data requires to find the set of \( (P, E, E_p) \) that minimizes equation 5.10 and results in the maximum slope of the adjusted supply limit. In order to account for the underlying data uncertainty and potential outliers, bootstrapping is used. The data cloud of a particular gridpoint is resampled 1000 times and for each sample the set of \( (P, E, E_p) \) that maximizes \( y_0 \) is selected. The median of all acquired \( y_0 \)-values is further used to estimate \( \kappa \) in a least squares fit.

The estimates of \((\kappa, y_0)\) provide a fixed set of parameters that represents the whole time period and are illustrated in Fig. 5.7. The \( \kappa \)-parameter is rather small in most subtropical desert regions and somewhat larger in tropical regions. Relatively large values of \( \kappa \) are further found in mid to high latitude regions. For \( y_0 \), lowest values are found in tropical and midlatitude regions, whereas subtropical and also subpolar areas show somewhat higher values. In summary, dry regions tend to show values of \( y_0 \) close to zero, denoting conditions similar to the original framework. It is further important to note that \( \kappa \) and \( y_0 \) are spatially not correlated.

To validate the performance of the model given by equation 5.10, the derived set of parameters at each gridpoint is used to model \( E \) within the calibration period (1990-2000). Correlations between the modeled time series derived by using the parameter set and the observed time series and anomaly correlations between ’detrended’ time series with removed annual cycles are shown in Fig. 5.8.

Generally, correlations are relatively large in many regions, whereas anomaly correlations are smaller. Largest correlations (>0.8) are found in all mid to high latitude regions. However, the most important feature regarding the time series of \( E \) in these regions is the annual cycle, which is well represented by the model. Hence, the first-order control on \( E \) regarding seasonal
5.5. ASSESSING THE FRAMEWORK WITH OBSERVATIONS

Figure 5.7: Estimated values of $\kappa$ (subfigure a) estimated in a least squares fitting after values of $y_0$ (subfigure b) were directly estimated from all data at each grid point using standard monthly datasets of $P$, $E$ and $E_p$ within the 1990-2000 period.

variations is robustly represented by variations in water supply $P$ and demand $E_p$. Further, correlations are, despite being still positive and relatively large (around 0.5), smaller in the inner tropics (central Amazonia and Congo Basin). This is most probably due to weak seasonal variations of $E$ and hence an increased importance of second-order controls on month-to-month changes in $E$.

Similar to the original Budyko framework, this is however not true for deviations from the mean, which are potentially subject to various second-order controls, as suggested by very small anomaly correlations in most regions. However, in some subtropical areas, anomaly correlations are reasonably large (up to 0.5).

An interesting feature is found regarding many monsoon regions (India, Southeast Asia, Northeast Brazil and the Sahel). The distinct difference between wet and dry seasons seems to prohibit the use of a fixed parameter set. The derived parameter set instead represents wet season characteristics as $y_0$ and consequently overestimates dry season $E$. These issues could be circumvented by calibrating separate parameter sets for either each month of the year, or dry and wet seasons in particular. Using estimates of $y_0$ derived from monthly climatologies and corresponding $\kappa$-values represents seasonal variations in the parameters themselves. By doing so, resulting correlations in monsoon regions are similar to those in mid and high latitude regions (see Fig. 5.8c). Interestingly, using the individual parameter sets derived from monthly climatologies instead of using a fixed parameter set for the whole time period, does not significantly increase the performance of the model in mid to high latitude areas. It does further not significantly increase the capability of the model to predict anomalies (comparing Fig. 5.8b and d).

To further highlight the differences between midlatitude and monsoon regions, the model performance is analysed in more detail for two regions: (i) central Europe and (ii) central Sahel (see Fig. 5.9, regions are highlighted
CHAPTER 5. NONSTATIONARY BUDYKO FRAMEWORK

Figure 5.8: Correlation between modeled $E$ and observed $E$ for a) the fixed estimated parameter set estimated for the whole time period and c) parameter sets derived from monthly climatologies. Anomaly correlations of the detrended time series after removing the annual cycle of $E$ are depicted in subfigure b) and d). Grey boxes indicate the regions featured in Fig. 5.7.

The upper two plots of Fig. 5.9 illustrate the respective data cloud of monthly values for both regions within the Budyko space. To note first, it is evident, that the original supply limit does not hold at monthly time scales as it is systematically overshot. The data cloud for central Europe shows an almost linear increase of $E/P$ with increasing $\Phi$, that is just slightly upset from the demand limit (thus implying a rather large $y_0$). For the central Sahel region, two regimes are noticeable. The first (during the winter months) being relatively similar to those of central Europe, with increasing $E/P$ close to the demand limit (large $y_0$) and therefore depicting wet season conditions. The second regime (during spring and summer months) remains within the bounds of the original Budyko framework, hence depicting conditions of no additional water other than $P$ available for $E$ (therefore implying $y_0$ being close to zero).

The comparison between modeled and observed $E$ reveals a rather good performance of the model for Central Europe ($R^2 = 0.87$, RMSE = 0.51). In the Sahel region, the fixed parameter set (see Fig. 5.9d) best represents the wet regime (as it determines the maximum slope), resulting in the model to overestimate dry season $E$. However, the model performs significantly better in the Sahel region if one explicitly accounts for seasonal variations in the parameter set (see Fig. 5.9f). For central Europe, however, it is evident that
5.5. ASSESSING THE FRAMEWORK WITH OBSERVATIONS

Figure 5.9: Data cloud of monthly values within the Budyko space for all grid-boxes in a) central Europe (45° N to 53° N, 5° E to 14° E) and b) parts of the Sahel (5° N to 12° N, 10° E to 19° E, see also Fig. 5.6). The black solid line denotes the demand limit, the dashed line denotes the original supply limit. c), d) Scatter plots of modeled vs. observed E using the fixed estimated parameter set and e), f) using the parameter sets derived from monthly climatologies, at each gridbox within the particular regions (left column: central Europe, right: Sahel). Months of the year are color-coded.
a monthly Climatology of parameter sets does not significantly improve the
model performance.

It is further important to note, that in some instances also the demand
limit is exceeded, occurring most probably due to data uncertainties regarding
the $E$ estimates and the $E_p$ parametrization.

5.6 Conclusions

Our study introduces a new, two-parameter Budyko-like model, which is
capable to represent non-stationary characteristics of $E/P$ and $E$. The origi-
nal Budyko framework is constrained to mean annual catchment scales, in
order to ensure a steady-state water balance. Here we assume, that on most
other spatio-temporal scales, the boundary condition constituted by the atmo-
spheric water demand remains, whereas the boundary condition constituted
by water supply is, besides $P$, also subject to water added (or withdrawn) via
storage changes. To account for this assumption, the derivation of Fu’s equa-
tion (Fu, 1981; Zhang et al., 2004) was modified accordingly and a similar
formulation including an additional parameter is obtained. Although the pa-
rameter in the original and the first parameter of our formulation are purely
mathematical, the additional parameter is physically well defined. Techni-
cally, the parameter rotates the original supply limit upwards. The frame-
work was validated by using global, monthly, gridded standard estimates of
$P$, $E$ and $E_p$. The prediction of $E$ using the model did represent seasonal dy-
namics for many parts of the world well by using a fixed parameter set over
the whole time period. However, in several monsoon regions, the distinct
difference between wet and dry seasons required enhanced parameter sets to
represent the particular hydrological conditions of each month/season.

Like the original Budyko framework, the derived two-parameter Budyko
model represents the influence of first-order controls (namely $P$ and $E_p$, or
in combination aridity index on water availability). Also, the combined influ-
ence of second-order controls (like e.g. vegetation, topography, etc.) are, com-
parable to Fu’s equation, integrated into the first parameter of the framework
($\kappa$ in the new framework, $\omega$ in Fu’s equation, respectively). Studying these
controls in Fu’s formula was subject to numerous studies, but no conclusive
assessment was conducted until present. Assessing the combined influence
of climatic and catchment controls is hence clearly beyond the scope of this
study. However, the additional second parameter of the new formulation $y_0$
is physically well defined as it represents a measure of additional water being
(besides $P$) available for $E$. But the availability of additional water is itself
subject to numerous controls and if no data is available, a direct estimation
of the parameter is initially not possible. Assessing these controls is, however,
subject to future research.

Finally we note that the available water that can compensate for lack
of $P$, i.e. soil moisture, ground water and other surface water sources can be more accurately assessed on a month-to-month basis when using a water balance model. The purpose of the present formulation is not to replace such modeling approaches but to promote a general framework accounting for non-stationary conditions within the Budyko relationship.

Further, Greve et al. (2015) recently suggested a probabilistic Budyko framework by assuming that the free parameter in Fu's equation is distributed. Similar assumptions could be applied to the two-parameter Budyko curve in future assessments, to allow for a better statistical representation of the scatter around the obtained curve.

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Conclusions and Outlook

6.1 Conclusions

The present thesis investigates past and projected changes to the mean climate state of hydroclimatological conditions at the land surface. Selected dataset combinations and climate models are thoroughly analysed by using a new approach based on the Mahalanobis distance to identify both robust changes in past and future dryness/wetness. Regarding the assessment of past changes, a large number of datasets is at first validated against the Budyko framework in order to select physically consistent combinations of data products. As a reference model to summarize first-order controls of atmospheric dryness and water availability within a powerful, but simple tool, the Budyko framework is both utilized and subject to further developments. In the present thesis, major limitations of the Budyko framework are addressed and new perspectives on it are provided.

In Chap. 2, trends in wetting and drying over global land are studied within a comprehensive assessment for the 1948-2005 time period. In order to address the methodological and data uncertainty, a variety of datasets is used and a new approach to concurrently analyse changes in both water availability and aridity is presented. The large number of datasets for precipitation $P$, evapotranspiration $E$ and potential evapotranspiration $E_p$ results in an even larger number of possible dataset combinations. To evaluate the physical consistency of arbitrary combinations, the Budyko framework
is used as a reference model to select reasonable data composites. The validation shows that highest uncertainty is attributed to evapotranspiration datasets. Changes in dryness/wetness are analysed using $P - E$ to assess trends in water availability and the aridity index $E_p/P$ to represent the interplay of atmospheric water supply and demand. The selected combinations of datasets are analysed following a new approach that takes the uncertainty of all components simultaneously into account and compares mean changes between the 1948-1968 and 1985-2005 time periods. It is thus possible to identify regions in which water availability and/or aridity are significantly changing (or not). Our results reveal that for ca. 3/4 of the land surface no robust trend is detectable. Within the remaining regions, significant drying is identified for e.g. parts of the Mediterranean region, East Asia and Africa and wettening in parts of North America and South America. By further identifying the distribution of humid and arid areas in the 1948-1968 time period using the aridity index, it is possible to determine if dry regions are drying out further and wet regions are becoming wetter. Hence, it is possible to comprehensively validate the well-known ‘dry gets drier, wet gets wetter’ (DDWW) paradigm. The results show that, in total, for only 11% of all land area the paradigm is supported. We conclude that the DDWW paradigm is not capable of reflecting the complexity of changes in hydroclimatological conditions adequately. It is further important to assess the underlying uncertainties comprehensively.

Chap. 3 addresses the argument that the DDWW paradigm could still apply to projected future changes in hydroclimatological conditions even if it does not necessarily apply to past changes (because of larger signal to noise ratio). The methodology developed in Chap. 2 is thus applied there to projected changes, based on the ensemble of CMIP5 climate models, comparing the 1980-1999 and 2080-2099 time periods. It is further important to note that the DDWW paradigm was mainly endorsed through the analysis of $P - E$. However, our results show that the $P - E$ metric alone is not appropriate to assess changes in dryness/wetness over global land. Robust wettening in $P - E$ is indeed found in some high latitude land regions, but no significant trends are identified in other regions. The $P - E$ metric is more appropriate over global ocean, with significant increases found in many midlatitude and tropical and significant decreases in subtropical ocean areas, consequently supporting the DDWW paradigm. Regarding changes on land it is further found that robust drying signals in many subtropical and adjacent land regions could be attributed to changes in aridity, which support previous findings of dryland expansion. Nonetheless, due to the large land area exhibiting no robust trend in either water availability or aridity (ca. 2/3 of all land surface) and the expansion of dry regions into formerly humid areas, especially north of the Mediterranean, we conclude that the DDWW paradigm is generally not applicable for projected changes. We point out a
few notable exceptions, which include a further drying of the Mediterranean region and a wettening of the northern high latitudes.

Still, a few issues remain disputable in these analyses even though a large number of available datasets is used in a statistically robust framework. In Chap. 2 and Chap. 3, changing dryness/wetness is assessed through the combination of changing water availability and aridity. We thereby consider the special hydroclimatological characteristics of the land surface, but do not explicitly incorporate other factors potentially influencing dryness/wetness trends, like e.g. changes in relative humidity or vegetation (Although these factors are at least implicitly taken into account since by definition potential evapotranspiration integrates the combined influence of all factors determining the energy constraint on evapotranspiration). Since no universal definition of dryness/wetness exists, it can still be argued that the combined metric used in the present thesis is more sophisticated than (i) other metrics relying on single variables only and (ii) metrics relying on single or combined variables without taking either supply or energy constraints explicitly into account.

Especially regarding Chap. 2, criticism could arise due to the fact that the identified trends are not directly related to climate change but subject to internal variability of the climate system. Even though the climate change signal in the period covered in Chap. 2 is rather small, it is still significant. Further, even under projected conditions of strong climate change in Chap. 3, the total area of robust trends remains rather small and does not generally support the DDWW paradigm.

Another difference between the assessments presented in Chap. 2 and Chap. 3 is not just the time period and the differing available data sources, but also the extensive validation of data combinations performed prior to the trend analysis in Chap. 2, whereas in Chap. 3 all available CMIP5 models are used. However, an extensive validation on physical consistency in Chap. 3 is initially not required, since the combinations of precipitation and evapotranspiration \( (P - E) \) and precipitation and potential evapotranspiration \( (E_p/P) \) are individually estimated from the same model, which implies an a priori consistency among these variables. Nonetheless, performing a similar validation procedure for the CMIP models in order to select models performing well from a hydroclimatological perspective could be the subject of future assessments (see also outlook in Sec. 6.2).

The Budyko framework served as a valuable tool in Chap. 2. Despite its decades-long history of hydrological relevance a few limiting issues remain, of which two are addressed in Chap. 4 and Chap. 5. These issues are (i) the nonlinearity of the underlying Budyko phase space and (ii) the limitation to steady-state conditions.

In Chap. 4, we refer to the brief literature review provided in Sec. 1.4.3, which provides an overview on potential controls shaping the Budyko curve
and deviations from the curve. The review shows that so far no conclusive statement about controls could be made. It further reveals that a large number of potential controls influences the scatter within the Budyko space, but their combined influence still remains highly uncertain. Also, deviations from the curve are usually determined in a euclidean sense, which is potentially misleading regarding the nonlinearity of the underlying phase space. We address these issues by using Fu’s formulation of the Budyko curve (Fu, 1981; Zhang et al., 2004). That formulation includes a free parameter (ω) without an a priori physical meaning. The parameter ω is usually interpreted to reflect the combined influence of various climatic and catchment parameters other than the aridity index. Since in our understanding the combined influence of all controls on ω is difficult to assess, we assume that this combined influence and consequently also ω is arbitrarily distributed. We make, however, no prior assumptions on the distributional form underlying ω. The assumption that ω follows a certain distribution enables us to introduce a probabilistic Budyko framework, which implicitly accounts for the scatter within the Budyko space. Thus, rather than computing a single value of E/P dependent on the aridity index, we are able to determine a probability distribution of E/P conditional on the aridity index. Hence, this approach explicitly accounts for the nonlinearity of the Budyko space. By using a set of catchments located within the United States we were able to estimate a distribution of ω and propose that ω potentially follows a gamma distribution. We argue, that the probabilistic framework most likely provides a powerful tool for future assessments on physical controls.

In Chap. 5, the limitation of the Budyko framework to steady-state conditions is addressed, which does not permit the use of the framework at sub-annual catchment scales. This limitation is a consequence of the fact that the water balance equation is assumed to be closed and storage changes are neglected, inducing the supply limit. Here, the equation of Fu (1981) is used, because it provides the most theoretically and mathematically sound formulation of the Budyko curve, being derived analytically from basic phenomenological assumptions rather than being derived entirely empirical. The underlying assumptions form a set of differential equations that are solved using the demand and supply limit as boundary conditions. The assumption that the water balance is not closed could thus easily be incorporated by relaxing one of the boundary conditions. Relaxing the boundary conditions requires an additional parameter, but the set of differential equations is still solvable. The resulting new formulation is similar to Fu (1981), but includes an additional second parameter. In contrast to ω, the new parameter retains an actual physical meaning and could be directly estimated from data. Technically, the new second parameter rotates the supply limit of the framework upwards and thus accounts for systematic overshoots of the original supply limit which occur on monthly and seasonal time scales. Hence, the
6.2. OUTLOOK

parameter regulates the amount of water that is available to evaporate water even if the water supply through precipitation is negligible. The framework is further validated using arbitrary monthly, gridded data estimates of precipitation, evapotranspiration and potential evapotranspiration and shows a surprisingly good performance.

Although the fundamental research conducted in Chap. 4 and Chap. 5 surely enhances the capabilities of the Budyko framework, still many research questions remain open, especially regarding physical controls and mechanisms which are not explicitly assessed in the present thesis. A discussion on potential future developments regarding the Budyko framework, also with respect to the advances made in Chap. 4 and Chap. 5 of the present thesis, is provided at the end of the next section. At first, an outlook onto potential future research regarding hydroclimatological changes with respect to Chap. 2 and Chap. 3 of the present thesis is given.

6.2 Outlook

Here, possible future research topics, from which some are already in preparation or being investigated, are suggested.

Hydroclimatological change under increasing CO$_2$:

A few studies (Sherwood and Fu, 2014; Fu and Feng, 2014) argue that a general increase in aridity is simply a thermodynamic consequence of a warming world. However, the results presented in Chap. 2 and Chap. 3 of the present thesis reveal a much more heterogeneous picture of changes in water availability and aridity in the recent past and within the 21st century. A study in preparation under my lead aims to compare mean climatic conditions in several hydrological components and dryness measures as a function of differing levels of external CO$_2$ forcing as performed in equilibrium model runs of CMIP5 experiments. The results potentially provide further insights on the common assumption of increasing dryness in a future world.

Validating the hydroclimatological performance of CMIP5 models:

In Chap. 2, all dataset combinations were validated against the Budyko framework to test on physical consistency. In Chap. 3, no validation was performed, since the combinations of precipitation, evapotranspiration and potential evapotranspiration originate from the same model and are thus assumed to be physically consistent. However, it is likely that the performance regarding hydroclimatological processes differs among the ensemble of CMIP5 climate models. Again, the Budyko framework could help to select climate models performing better than others. Thus, an assessment on projected changes in dryness/wetness could be constrained to models performing well within the Budyko framework compared to observations in the historical
CHAPTER 6. CONCLUSIONS AND OUTLOOK

period (in effect mostly validating the representation of the $\omega$ parameter in the models). This would potentially help to (i) increase the significance of detected trends, to (ii) identify spurious trends caused by models with unrealistic representation of hydroclimatological processes, and to (iii) propose a list of realistic CMIP5 models which could be used in future assessments on land hydrological changes.

Implications of mean annual hydroclimatological changes on seasonal changes and climatic extremes: In Chap. 2 and Chap. 3 of the present thesis, changes in dryness/wetness have been assessed on mean annual time scales. However, a few studies suggest that there is a potential redistribution of water within years. Chou et al. (2013) and Murray-Tortalo et al. (submitted to Nature Geoscience, a study to which I contributed as a co-author) suggested wetter wet seasons on the cost of drier dry seasons. Potential implications on seasonal changes resulting as a consequence from the findings regarding mean annual changes could provide further insights on the underlying physical mechanisms and drivers. Also the influence of robust wettening/drying trends on temperature and hydrological extremes is potentially of major interest.

A reference distribution of second order controls within the Budyko framework: In Chap. 4 a probabilistic Budyko framework was introduced. In this approach, the free parameter $\omega$ in Fu’s formulation of the Budyko curve (Fu, 1981) was assumed to be distributed in order to represent the combined influence of all landscape and catchment characteristics exerting control on deviations from the original Budyko curve. In Chap. 4, we estimate the underlying distribution of $\omega$ for a set of ca. 400 catchments in the United States. In a next step, it would be of interest to estimate a distribution of $\omega$ for other sets of catchments to finally assess controls shaping the distributional form of $\omega$ itself. Also, a global reference distribution could potentially be estimated. A literature review of studies using Fu’s formulation will provide an appropriate source of $\omega$-values from catchments around the world. This topic will be covered in a Master thesis project which I will co-supervise.

Controls on the two-parameter nonstationary Budyko framework: In Chap. 5, a two-parameter Budyko curve also applicable under nonstationary conditions is derived. Despite its similarity to the original stationary formulation of Fu (1981), it includes an additional parameter. However, the first parameter ($\kappa$) is potentially, but not necessarily, similar to the $\omega$-parameter in Fu’s equation. Also, the second parameter, even though it is clearly defined, may represents certain processes of the hydroclimatological system. It would thus be useful to conduct further in-depth research on
potential controls shaping the derived new two-parameter Budyko curve.

**A review paper on the Budyko framework:** As part of a small group of early-career scientists I am currently co-leading the preparation of an extensive review paper on the Budyko framework (see also Sec. 1.4). The fundamental research conducted in Chap. 4 and Chap. 5 and the variety of recent new studies using the framework as presented in Sec. 1.4.3 shows the necessity of a comprehensive review on this topic. A large part of the review will further be dedicated to an outlook on potential future uses of the framework, also in other fields than hydrology alone. With Chap. 4 and Chap. 5, two engaging examples on how the framework could potentially be enhanced are provided, opening the floor for a number of future uses. Large parts of the introduction on the Budyko framework provided in Chap. 1 are based on my prepared contribution to the review paper.
Appendix to Chapter 2

A.1 Data

Our validation relies on the Budyko framework, which relates $E/P$ to $E_p/P$. Sections A.1.1, A.1.2 and A.1.3 provide details of the investigated $P$, $E$ and $E_p$ datasets, respectively. The Budyko formulation by Fu (1981) contains the free parameter $\omega$ being related to climatological NDVI (Li et al., 2013), which we adjust according to NDVI data from the Global Inventory Modeling and Mapping Studies (GIMMS) (Tucker et al., 2005). The $P$, $E$ and $E_p$ datasets are also used to analyse dryness changes with respect to the land water balance ($P$ vs. $E$) and the hydroclimatic regime ($P$ vs. $E_p$).

A.1.1 Precipitation datasets

We use global monthly datasets of precipitation ($P$) and evapotranspiration ($E$) to investigate changes in the land water balance. All $P$ datasets are based on observations, either interpolated gauge observations only or combined with satellite measurements. All $P$ datasets are listed in Table A.1.
Table A.1: P datasets in this study. All datasets cover the shorter validation period (1984 - 2005). The datasets which do not cover the longer period of the dryness change analysis (1948-05) are marked with a star. We interpolated all datasets to a common regular 0.5° grid.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Characteristics</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRU</td>
<td>interpolated gauge observations, no bias adjustment</td>
<td>Harris et al. (2013)</td>
</tr>
<tr>
<td>GPCC</td>
<td>interpolated gauge observations, no bias adjustment</td>
<td>Rudolf et al. (2005)</td>
</tr>
<tr>
<td>GPCP*</td>
<td>interpolated gauge observations combined with satellite data, bias adj.</td>
<td>Adler et al. (2003)</td>
</tr>
<tr>
<td>UDel P</td>
<td>interpolated gauge observations</td>
<td>Legates and Willmott (1990)</td>
</tr>
<tr>
<td>PREC/L</td>
<td>interpolated gauge observations, no bias adjustment</td>
<td>Chen et al. (2002)</td>
</tr>
<tr>
<td>CPC*</td>
<td>interpolated gauge observations combined with satellite data, no bias adj.</td>
<td></td>
</tr>
</tbody>
</table>

A.1.2 Evapotranspiration datasets

We use global monthly E datasets from various sources. Within the 1984-2005 validation period three observations-based 'diagnostic' datasets are available. However, most other E datasets are model-based, either driven by observations-based or reanalysis-based forcing. Notably, we use data from the TRENDY project (Sitch et al., 2013) including six state of the art LSMs. All E datasets are listed in Table A.2. The subdivision of E datasets into different classes follows the notation of Mueller et al. (2011).

A.1.3 Potential evaporation parameterization

Hydroclimatological regime shifts are found by analysing potential evaporation \( (E_p) \) in conjunction with \( P \). We use several methods of differing complexity to determine \( E_p \) from temperature and/or net radiation (see Table A.3). The method of Priestley-Taylor (Priestley and Taylor, 1972) approximates \( E_p \) as

\[
E_p = \frac{\alpha}{\lambda} \left( \frac{\Delta \cdot (R_n - G)}{\Delta + \gamma} \right),
\]

with \( \lambda \) being the latent heat of vaporization \( (\lambda = 2.45 \text{MJkg}^{-1}) \), \( \gamma \) the psychrometric constant \( (\gamma \approx 0.054 \text{kPa}/\text{°C} \text{ for an average air pressure of } 1013.25 \text{hPa}) \) and \( G \) the ground heat flux \( (G \text{ could be neglected following Weiß and Menzel, 2008}) \). The term \( \Delta \) is the slope of the saturation water vapor pressure curve (depending on \( T \) only) and estimated by the Tetens-Murray equation (Murray, 1967). The term \( \alpha = 1.26 \) is the Priestley-Taylor constant as suggested by Priestley and Taylor (1972). However, Maidment (1993) found that \( \alpha = 1.26 \) is suitable for humid climates only and that \( \alpha = 1.74 \) for
Table A.2: $E$ datasets in this study. All datasets cover the shorter validation period (1984 - 2005). The datasets which do not cover the longer period of the dryness change analysis (1948 - 2005) are indicated with a star. We interpolated all datasets to a common regular 0.5° grid. For detailed information on the individual datasets the reader is referred to the given references. Further information on the TRENDY project is provided in Sitch et al. (2013)

<table>
<thead>
<tr>
<th>Variable/Class</th>
<th>Dataset</th>
<th>Characteristics</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagnostic</td>
<td>MPI-BGC</td>
<td>Statistical upscaling of flux observations derived from the Budyko framework with observed $P$ and Penman-Monteith $E_P$</td>
<td>Jung et al. (2010)</td>
</tr>
<tr>
<td></td>
<td>CSIRO*</td>
<td>Priestley and Taylor based algorithm based on satellite observations only</td>
<td>Leuning et al. (2008); Zhang et al. (2010)</td>
</tr>
<tr>
<td></td>
<td>GLEAM*</td>
<td>Priestley and Taylor based algorithm based on satellite observations only</td>
<td>Miralles et al. (2011)</td>
</tr>
<tr>
<td>LSMs</td>
<td>VIC</td>
<td>forced with improved NCEP reanalysis data from Sheffield et al. (2006)</td>
<td>Liang et al. (1994)</td>
</tr>
<tr>
<td></td>
<td>NOAH</td>
<td>forced with improved NCEP reanalysis data from Sheffield et al. (2006)</td>
<td>Chen and Dudhia (2001); Ek et al. (2003)</td>
</tr>
<tr>
<td>TRENDY</td>
<td>SDGVM</td>
<td>forced CRU observations, merged with NCEP reanalysis data</td>
<td>Woodward and Lomas (1995); Oleson et al. (2010); Zaehele and Friend (2010); Zaehele et al. (2011)</td>
</tr>
<tr>
<td>LSMs</td>
<td>CLM</td>
<td>forced CRU observations, merged with NCEP reanalysis data</td>
<td>Smith et al. (2001)</td>
</tr>
<tr>
<td></td>
<td>Orchidee-CN</td>
<td>forced CRU observations, merged with NCEP reanalysis data</td>
<td>Cox (2001)</td>
</tr>
<tr>
<td></td>
<td>LPJ-GUESS</td>
<td>forced CRU observations, merged with NCEP reanalysis data</td>
<td>Levy et al. (2004)</td>
</tr>
<tr>
<td></td>
<td>TRIFFID</td>
<td>TRENDY forcing, Sitch et al. (2013)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>HYLAND</td>
<td>TRENDY forcing, Sitch et al. (2013)</td>
<td></td>
</tr>
<tr>
<td>Reanalysis</td>
<td>ERA-Interim*</td>
<td>no data-assimilation of observed precipitation</td>
<td>Dee et al. (2011)</td>
</tr>
<tr>
<td></td>
<td>NCEP-CFSR*</td>
<td>no data-assimilation of observed precipitation</td>
<td>Saha et al. (2010)</td>
</tr>
<tr>
<td></td>
<td>MERRA*</td>
<td>no data-assimilation of observed precipitation</td>
<td>Rienecker et al. (2011)</td>
</tr>
<tr>
<td></td>
<td>NCEP</td>
<td>no data-assimilation of observed precipitation</td>
<td>Kanamitsu et al. (2002)</td>
</tr>
<tr>
<td></td>
<td>20CR</td>
<td>no data-assimilation of observed precipitation, only assimilating surface air pressure and sea surface temperature</td>
<td>Compo et al. (2011)</td>
</tr>
</tbody>
</table>
Table A.3: $T$ and $R_n$ datasets in this study. All datasets cover the shorter validation period (1984 - 2005). The datasets which do not cover the longer period of the dryness change analysis (1948-05) are marked with a star. We interpolated all datasets to a common regular $0.5^\circ$ grid.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Dataset</th>
<th>Characteristics</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T$</td>
<td>UDel (D)</td>
<td>interpolated station data</td>
<td>Legates and Willmott (1990)</td>
</tr>
<tr>
<td></td>
<td>CRU (C)</td>
<td>interpolated station data</td>
<td>Harris et al. (2013)</td>
</tr>
<tr>
<td>$R_n$</td>
<td>SRB* (S)</td>
<td>satellite derived</td>
<td>Legates and Willmott (1990)</td>
</tr>
<tr>
<td></td>
<td>ERA-I* (E-I)</td>
<td>ERA-Interim reanalysis</td>
<td>Dee et al. (2011)</td>
</tr>
<tr>
<td></td>
<td>NCEP (N)</td>
<td>NCEP/NCAR reanalysis</td>
<td>Kanamitsu et al. (2002)</td>
</tr>
<tr>
<td></td>
<td>20CR (2)</td>
<td>20th century reanalysis</td>
<td>Compo et al. (2011)</td>
</tr>
</tbody>
</table>

Arid climates avoids underestimation of $E_p$. We use here both approaches, denoted as PTc (constant $\alpha$) and PT (adjusted $\alpha$), as both approaches are widely used. For PT, $\alpha$ is adjusted according to the Köppen-Geiger climate classification. We use a classification from Rubel and Kotte (2010), which is in very good agreement with Peel et al. (2007). This classification uses $\alpha = 1.26$ for tropical (group A), continental (group D) and humid mild temperate climates (Cfa, Cfb, Cfc, Cwa and Cwb), and $\alpha = 1.74$ for dry (group B) as well as polar (group E) and arid mild temperate climates (Csa and Csb).

The Penman-Monteith method (Monteith, 1965) is the most sophisticated and widely used method to determine $E_p$ in LSMs. However, additional input variables other than $T$ and $R_n$ are required for its computation (like e.g. wind speed, relative humidity and vegetation properties) and thus we use a pre-compiled dataset (Sheffield et al., 2012).

$R_n$ essentially controls $E_p$ and we are thus able to estimate $E_p$ directly from $R_n$ using $\lambda$ by

$$E_p = \frac{R_n}{\lambda}.$$  \hspace{1cm} (A.2)

Despite its simplicity, $R_n/\lambda$ performs similarly well compared to the other more sophisticated approximations (see Fig. 2). Due to the widespread availability of $R_n$ measurements, this approach is commonly applied.

Several studies suggest that temperature-based $E_p$ estimates should not be used for trend analysis (Sheffield et al., 2012). Hence, we do not use such $E_p$ estimates (see main text). Nonetheless, our results remain similar after including the still widely used methods of Thornthwaite (1948) and Blaney and Criddle (1964) in our analysis, which rely on temperature only. Evaluation of these methods also reveals a reasonable performance (not shown).
A.2 Dryness metrics

The analysis of Held and Soden (2006) reveals drying ($\Delta(P - E) < 0$) in dry oceanic regions ($P - E < 0$) and wetting ($\Delta(P - E) > 0$) in wet oceanic regions ($P - E > 0$). This definition is problematic over land as $P - E \Rightarrow 0$ by definition (which is clearly illustrated in figure A.1 which contrasts both the projected zonal changes and present-day zonal mean P-E over the oceans vs. land for an arbitrary set of 35 CMIP5 GCMs). This means technically all land regions are wet and the DDWW paradigm is not applicable. Held and Soden (2006) note this limitation, hence their article is not the main source of problem, but rather the perception of their results in the general public. This raises the need for other definitions to apply the DDWW over land and with this study we aim to overcome this issue by using a well established method of classifying arid and humid land regions (the aridity index). This approach dates back to Budyko (1974) and is very well established in land hydrology. Consequently, changes in dryness are found by analyzing (1) changes in $P - E$ (Held and Soden, 2006) and (2) changes in the aridity index to consider a measure relevant to land hydrology. By doing so we give consideration to the different hydroclimatological characteristics of the land surface, as the available water is limited there by water storage and water supply and thus both changes in the water supply ($P$) and storage depletion/accumulation (changes in $E/Ep$) need to be jointly considered (which is not the case over the oceans). We therefore highlight that the traditional approach of Held and Soden (2006) needs to be extended over land in order to take the additional physical properties of the land surface into account.
Figure A.1: The zonal mean $\Delta(P - E)$ (1980-99 vs 2080-99, top panel) and $P - E$ of the present climate (1980-99, middle panel) from the ensemble mean of 35 CMIP5 model runs (black), for ocean grid points only (blue) and for land grid points only (green). The shading denotes the ensemble standard deviation. The overall result (black line) corresponds very well to the finding of Held and Soden (2006). However, the distinction between land and ocean grid points reveals fundamental differences. Over land the zonal mean drying trends are, if any, very small and not significant in subtropical regions. The figure clearly shows that the overall signal (Held and Soden, 2006) is dominated by the ocean signal (which makes sense regarding the unequal distribution of zonal land area vs. ocean area, bottom panel). The figure further shows that $P - E > 0$ over land and thus technically all land regions are wet (middle panel).
A.3 Evaluation for the 1948-2005 period

To assess the sensitivity of the results on the time period chosen for the evaluation, and for consistency with our analysis of dryness changes over the 1948-2005 period, we evaluate here 9 $E$ and 4 observations-based $P$ datasets together with 11 estimates of $E_p$ over the 1948-2005 period, resulting in a total number of 396 combinations. The validation is performed using the same methodology as for the 1984-2005 period (see Methods and Table 1.1, A.2 and A.3).

The RMSwE’s of all combinations containing a certain $E$, $P$ or $E_p$ dataset are shown in Fig. A.2. Most $E$ datasets that are found at the top of the panel (i.e. with smallest RMSwE’s) also display the smallest RMSwE’s for the short analysis period (Fig. 2) and show lower error measures compared to those at the bottom of the panel, independently of the choice of $P$ and $E_p$. The largest median RMSwE (1.75, see the boxplot for the NCEP Reanalysis in Fig. A.2a) is almost eight times larger than the lowest value (0.23 for the VIC LSM). Here, $E$ datasets are clearly subdivided into two performance categories, whereby eight of the nine data sets with relatively low median values belong to the category of LSMSs driven by an observations based forcing (green and blue color). The effect of the choice of the $P$ and $E_p$ datasets is on the contrary almost negligible. However, the results are very similar compared to those shown in the main text and underline the robustness of our methodology.
Figure A.2: Budyko validation of hydrological dataset combinations for the 1948-2005 period. Boxplots of all RMSwEs related either to a) an individual $E$ or b) $P$ dataset and c) the $E_p$ estimates. Colors for the $E$ datasets denote the different classes (Mueller et al., 2011): LSMs with various forcings: green, LSMs from the TRENDY project (Sitch et al., 2013) (TR): blue, reanalysis: yellow. Dashed vertical lines illustrate the absolute minimum, the overall median and absolute maximum RMSwE (from left to right). See text and Methods for more information.
A.4 Dryness changes analysis for other time periods

In our study, we detect changes in the mean hydroclimatological conditions between the time periods 1948 to 1968 and 1985 to 2005. Changes on shorter time scales are potentially influenced by internal climate variability and are thus not used to detect long-term trends. However, in the interest of completeness we performed the same analysis comparing the first (1948-1968) and the last period (1985-2005) with the respective middle period (1968-1985, see Fig. A.3).

Comparing the first two periods reveals drying trends across the Sahel and other parts of Africa, in East Asia and the Mediterranean. Wetting appears in parts of North and South America, Northern Europe, West Asia and North Australia.

Comparing the last periods shows drying trends in many parts of Central Africa, Northeast Brazil, Mexico, the Mediterranean, the Middle East and various parts of Asia. Wetting trends are found in some parts of South America, the eastern US, northern Asia and the Sahel region.

Following these results, strongest changes took place between the first and the middle period and are just partly intensified between the last periods. However, some regions showing non-significant long-term trends experienced significant wetting first, followed by significant drying (like e.g. in Mexico or Middle East/Central Asia), possibly caused by internal variations.
Figure A.3: Drying/wetting trends analysed comparing (a) the 1948-1968 and the 1968-1985 and (b) the 1968-1985 and the 1985-2005 period applying the same methodology as for the long period shown in Fig. 4a. Dark red (dark blue) denotes a significant change towards drier (wetter) conditions both regarding the land water balance and hydrological regime shifts. Red/orange shows a shift towards more arid conditions. Drying due to changes in the land water balance only is depicted by green/pink color.
A.5 Sensitivity to the choice of the significance level

Our analysis was conducted using a significance level of 5% ($p < 0.05$). Choosing a different significance level (see Supplementary Methods) certainly affects the amount of total land area experiencing significant changes (for $p < 0.01$: 86.4% and for $p < 0.1$: 67.7%). Shown in Fig. A.4 and Fig. A.5 are results obtained by performing the analysis with $p < 0.01$ and $p < 0.1$. The basic findings remain similar, apart from the expected increase/decrease of total area with significant change. However, the results underline the robustness of the DDWW evaluation, as the percentage of global land with valid or invalid DDWW is independent from the choice of the significance level.
Figure A.5: Same as Fig. 4, but with setting the significance level to 10% ($p < 0.1$).
A.6 Alternative dryness change analysis

In order to assess the robustness of the outcomes from our dryness change analysis we directly investigate changes in $\Delta(P - E)$ and the aridity index $\Delta(E_p/P)$. These measures are one-dimensional, requiring other test statistics. For $E_p/P$ (and $P - E$ analogously) the empirical distribution generated by all possible $E_p/P$ combinations of a particular period is unknown, we therefore use a bootstrap hypothesis test to identify significant changes. We resample the median difference between both periods (48-68 vs. 85-05) $\Delta(E_p/P)$ 1000 times by drawing bootstrap samples from the merged sample of both periods and calculating $\Delta(E_p/P)'$ for each sample. If $\Delta(E_p/P)' > \Delta(E_p/P)$ if $\Delta(E_p/P) < 0$ (or vice versa) occurs less than 5 times ($p < 0.01$), we consider $\Delta(E_p/P)$ as significantly different from 0. The same approach identifies significant changes in $P - E$.

The results shown in Fig. A.6 are qualitatively similar to those shown in Fig. 4. Both methods reveal significant trends in the same regions, but the overall area of significant change is larger for the alternative test (18% vs. 24.6%). This is due to different statistical power of each test and different significance levels. However, the use of different significance levels does not change the distribution of area fraction supporting or not-supporting the DDWW paradigm (not shown).

Furthermore, other test statistics like a classical two-sample t-test (which is not a good choice since normality is not always given) or the non-parametric Kolmogorov-Smirnov test (which has a rather low statistical power) show similar results (not shown). Hence, our findings are robust and do not depend on the choice of test statistics.
Figure A.6: Investigating the DDWW paradigm by analysing $\Delta$-changes in $P - E$ and $E_p/P$. a) Significant drying/wetting trends computed at the grid box level with significance determined via a bootstrap hypothesis test. b) Distribution of arid (orange) to humid (blue) areas within the period from 1948-1968. c) Comparing the changes in a) with the hydrological conditions of the 1948-1968 period in b) evaluates the ‘dry gets drier, wet gets wetter’ paradigm.
Appendix to Chapter 3

B.1 Sensitivity of the results on the choice of a threshold to divide between arid/humid regions

In this study, arid/humid regions are classified by using $R_n/(\lambda P) = 2$ as a threshold value. Following this approach, regions with $R_n/(\lambda P) < 2$ are classified as humid, whereas regions with $R_n/(\lambda P) > 2$ are classified as arid. This definition is based on common definitions, that are also recommended by the United Nations Environment Programme (UNEP). Following this definition, the domain $1.5 < R_n/(\lambda P) < 2$ is referred to as the ‘subhumid’ and the domain $2 < R_n/(\lambda P) < 5$ is referred to as ‘semi-arid’. However, if we identify that the ensemble of all models at a particular gridpoint is not significantly different from $R_n/(\lambda P) = 2$, the gridpoint is classified as transitional.

Nonetheless, to choice of $R_n/(\lambda P) = 2$ is still somewhat arbitrary. Shown in Fig. B.1 and B.2 are results obtained for different threshold values of $R_n/(\lambda P) = 1.5$ and $R_n/(\lambda P) = 2.5$. Naturally, the distribution of arid/humid areas changes accordingly, with less humid/more arid areas for a threshold of $R_n/(\lambda P) = 1.5$ (see Fig. B.1b) and more humid/less arid areas for a threshold of $R_n/(\lambda P) = 2.5$ (see Fig. B.2b). However, the percentage values of regions confirming the paradigm or not (Fig. B.1c,d and Fig. B.2c,d) are very similar between both cases, showing that the main results presented in this study are rather insensitive to the choice of a threshold value to divide between arid and humid regions. It is further important to note that for
threshold values lower (larger) than 1.5 (2.5) the obtained distributions of arid/humid regions is highly unrealistic (not shown).

Figure B.1: Investigating the DDWW paradigm (similar to Fig. 4 but with $R_n/(\lambda P) = 1.5$ as threshold value). a) Significant drying/wetting trends computed at the grid box level. Dark red (dark blue) denotes a significant change towards drier (wetter) conditions both regarding the land water balance and hydrological regime shifts. Red/orange shows a shift towards more arid conditions. Drying due to changes in the land water balance only is depicted by green/pink color. b) Distribution of arid (orange) to humid (blue) areas within the period from 1980-2000. Beige colors denote transitional areas where no significant attribution is possible. c) Comparing the changes in a) with the hydrological conditions in b) yields an evaluation of the ‘dry gets drier, wet gets wetter’ paradigm. Red/dark blue colors indicate regions where the paradigm is found to be valid. Humid areas getting drier (orange) are widely found. d) Conceptual evaluation of the DDWW, with areas confirming (dark grey) and invalidating (black) the paradigm compared to areas showing no robust trend. Note that Antarctica is not accounted for in the subplots.
B.1. SENSITIVITY OF THE RESULTS ON THE CHOICE OF A THRESHOLD TO DIVIDE BETWEEN ARID/HUMID REGIONS

Figure B.2: Investigating the DDWW paradigm (similar to Fig. 4 but with $R_n/(\lambda P) = 2.5$ as threshold value). a) Significant drying/wetting trends computed at the grid box level. Dark red (dark blue) denotes a significant change towards drier (wetter) conditions both regarding the land water balance and hydrological regime shifts. Red/orange shows a shift towards more arid conditions. Drying due to changes in the land water balance only is depicted by green/pink color. b) Distribution of arid (orange) to humid (blue) areas within the period from 1980-2000. Beige colors denote transitional areas where no significant attribution is possible. c) Comparing the changes in a) with the hydrological conditions in b) yields an evaluation of the ‘dry gets drier, wet gets wetter’ paradigm. Red/dark blue colors indicate regions where the paradigm is found to be valid. Humid areas getting drier (orange) are widely found. d) Conceptual evaluation of the DDWW, with areas confirming (dark grey) and invalidating (black) the paradigm compared to areas showing no robust trend. Note that Antarctica is not accounted for in the subplots.
B.2 Seasonal DDWW

The results in this study are based on multi-year averages. Nonetheless, certain seasonal trends in $P - E$ and $P - R_n/\lambda$ might cancel out in this case. Therefore we provide here also seasonal estimates of changes in $P - E$ and $P - R_n/\lambda$ (see Fig. B.3). Drying occurs throughout the year e.g. in the Mediterranean region. However, drying conditions that were identified at mean-annual time scales in central/eastern Europe and central Asia are mainly induced by drier condition during boreal summer due to an corresponding changes in $P - R_n/\lambda$. Wetting conditions in the northern high-latitudes are mainly induced through significant changes in $P - E$ during boreal fall and winter. It is important to note here that, except for some regions in Siberia, no counteractive trends (like e.g. wetting in winter vs. drying in summer) are found.

![Figure B.3](image)

Figure B.3: Significant drying/wetting trends computed at the grid box level for a) MAM, b) JJA, c) SON and d) DJF. Dark red (dark blue) denotes a significant change towards drier (wetter) conditions both regarding the land water balance and hydrological regime shifts. Red/orange shows a shift towards more arid conditions. Drying due to changes in the land water balance only is depicted by green/pink color.
B.3 Future hydroclimatological changes based on Priestley-Taylor potential evapotranspiration

In this study, the aridity index was calculated as $R_n / (\lambda P)$. However, the aridity index is usually defined as $E_p / P$, with $E_p$ being potential evaporation. Here we used $R_n$ instead of $E_p$ for two reasons: (i) $E_p$ is, in contrast to $R_n$, not a standard output in the CMIP5 archives, and (ii) other approaches to estimate $E_p$ are assumed to be less robust under conditions of significant climate change (see Data and Methods section). However, here we also present results based on the well-established Priestley-Taylor method to estimate $E_p$.

The obtained results are qualitatively similar to those obtained in the main text. Trends in $E_p$ are showing significant increases for all land area (see Fig. B.4). The area of significant aridity change ($\Delta P - E_p$) is, however, larger when using Priestley-Taylor $E_p$, showing a total of 45.4% of all land area experiencing a significant shift either towards more arid or humid conditions within the 21st century. A shift towards more humid conditions takes place in 7.8% of global land area, entirely located in the northern high latitudes. A significant change towards more arid conditions is instead found for 37.6% of all land area. These changes are generally located in central North America, Middle America, Amazonia, southern and northern Africa, southern Europe, the Middle East, and central Asia, as well as southern Australia.

Combining both metrics, $P - E$ and $P - E_p$, results in a total of 51.8% of all land area experiencing a significant hydroclimatological change (see Fig. B.5).

Similarly to the analysis based on $R_n / \lambda$, the DDWW paradigm is confirmed for humid areas projected to experience a significant increase in water availability in the high latitudes. Further, a significant increase in aridity in many subtropical areas confirms the paradigm for dry desert regions in Africa, eastern Asia, and Australia. However, the DDWW is invalidated for a larger fraction of affected neighboring areas which are currently in a humid or transitional climate regime. These areas include large parts of southern and central Europe, but also region in central Asia, southern Africa and especially also North America. Drying conditions are additionally found in humid tropical Amazonia.

In summary, the DDWW using $E_p$ estimated via the Priestley-Taylor method is confirmed for only ca. 25% of all land area, whereas the DDWW is invalidated for another ca. 25%, and no trend is detectable in the remaining 50% of all land area (see Fig. B.5d).

Hence, using Priestley-Taylor estimates of $E_p$ supports the findings presented in Chapter 2. Indeed, the DDWW paradigm is even invalidated for a larger fraction of land area, especially including also regions in North America.
Figure B.4: Aridity changes within the 21st century based on the Priestley-Taylor method to estimate \( E_p \). a) Changes in \( P - E_p \) comparing present-day (1980-2000) and future climate (2080-2100) following the RCP8.5 pathway and b) changes in Priestley-Taylor \( E_p \). Stippling denotes regions where the change is significant at the 95%-level.
The future hydroclimatic changes are based on the Priestley-Taylor potential evapotranspiration. Figure B.5: Investigating the DDWW paradigm (similar to Fig. 4 but with $E_p$ estimated via Priestley-Taylor). a) Significant drying/wetting trends computed at the grid box level. Dark red (dark blue) denotes a significant change towards drier (wetter) conditions both regarding the land water balance and hydrological regime shifts. Red/orange shows a shift towards more arid conditions. Drying due to changes in the land water balance only is depicted by green/pink color. b) Distribution of arid (orange) to humid (blue) areas within the period from 1980-2000. Beige colors denote transitional areas where no significant attribution is possible. c) Comparing the changes in a) with the hydrological conditions in b) yields an evaluation of the ‘dry gets drier, wet gets wetter’ paradigm. Red/dark blue colors indicate regions where the paradigm is found to be valid. Humid areas getting drier (orange) are widely found. d) Conceptual evaluation of the DDWW, with areas confirming (dark grey) and invalidating (black) the paradigm compared to areas showing no robust trend. Note that Antarctica is not accounted for in the subplots.
Appendix to Chapter 4

C.1 Uncertainty of distribution parameters

In Chapter 4, we bootstrapped the uncertainty accompanying the computation of the shape $k$ and scale $\theta$ parameter from the sample of MOPEX catchments. This provides a range of uncertainty which however does not imply major changes on the basic characteristics of the estimated gamma distribution and thus supports the assumption of fitting a gamma distribution. Table C.1 provides estimates of the 2.5%, 50% and 97.5% quantile of the bootstrapped distribution parameters.

Table C.1: The 2.5%, 50%, best estimate and 97.5% quantile of the bootstrapped distribution parameters estimated from 1000 samples from the set of MOPEX catchment.

<table>
<thead>
<tr>
<th>2.5%</th>
<th>50%</th>
<th>best estimate</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k$</td>
<td>3.77</td>
<td>4.52</td>
<td>5.49</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.3</td>
<td>0.37</td>
<td>0.44</td>
</tr>
</tbody>
</table>

From table C.1 follows, that 95% of all $k$ lie within (3.77, 5.49) and all $\theta$ within (0.3, 0.44). This does indeed suggest a large variety of resulting gamma distributions and corresponding median values. Calculating the median (via
the approximation formula \((k, \theta) \ast ((3k - 0.8)/(3k + 0.2)))\) by using either the 2.5% or the 97.5% quantiles of \((k, \theta)\) from table C.1 shows a spread of +/- 0.5 for \(\omega\), which is indeed large. However, it is important to note that the actual uncertainty range of \(\omega\) is much smaller (ca. +/- 0.07, standard deviation is ca. 0.036) for the following reasons. First, the bootstrapped estimates of \(k\) and \(\theta\) are highly correlated \(r(k, \theta) = -0.96\), indicating that a low shape parameter is most probably found in combination with a larger scale parameter. Thus, an important issue is also propagation of uncertainty. Since an analytical solution of error propagation for the median calculation is not feasible, we provide the histogram of the bootstrapped median estimates to show that the actual range of \(\omega\) is indeed smaller (see Fig. C.1).

![Histogram of 1000 bootstrapped estimates of median \(\omega\)](image)

**Figure C.1:** Histogram of 1000 bootstrapped estimates of median \(\omega\)

Also, a cross-validation was performed. To increase the significance of a standard 10-fold (or k-fold in general) cross validation, we have randomly chosen 10,000 training samples from the set of MOPEX catchment. Each of the training samples contains 90% of the data and is used to estimate the parameters of the gamma distribution representing the distribution of \(\omega\) following a maximum likelihood approach. Validation against the empirical distribution of \(\omega\) for the residual 10% of catchments is performed using both the Anderson-Darling (AD) and the Cramer-von Mises (CvM) goodness-of-fit test metric. The percentage of data for which the parametrized gamma distribution cannot be ruled out to represent the empirical distribution of the remaining catchments at a 0.05% significance level is for AD: 92.5% and for CvM: 93.5%. This actually means that in more than 90% of all cases the parametrized gamma distribution of a certain set of MOPEX catchments does also represent the distributional characteristics of another set of MOPEX catchments and thus provides evidence on the validity of the assumption that \(\omega\) very likely follows a gamma distribution.
C.2 Probabilistic evaluation of datasets

The probabilistic framework introduced in Chapter 4 could be seen as an improvement of the original framework. The original framework was, however, used to evaluate combinations of hydroclimatological datasets in Chapter 2. Thus, in order to extend the evaluation approach, we perform here an evaluation of the respective dataset combinations by using the probabilistic framework.

To evaluate dataset combinations in a probabilistic procedure, the empirical distribution of $\omega$-values for each individual combination is estimated numerically. We use here the Kolmogorov-Smirnov nonparametric test to determine the equality between the empirical distribution of each combination and the Gamma distribution obtained from the comprehensive set of MOPEX catchments presented in Chapter 4. We use here the Gamma distribution of the MOPEX catchments as reference since no global distribution of $w$-values is available until present and the high quality set of MOPEX catchments covering a large variety of climate zones, potentially provides a reliable estimate. The Kolmogorov-Smirnov (KS) test identifies the maximum distance between the reference cumulative distribution function (CDF) and the empirical CDF of each combination. Hence, a large KS test statistic denotes a large inequality between the reference and the empirical distribution.

It is important to note that $\omega$-values are only defined within the water supply and demand limits. Most combinations also feature data points outside the limits. These data points are, however, ignored while performing the KS test. Nonetheless, combinations containing a large fraction of data points outside the physical limits generally also show higher KS test statistics (see in Fig. C.2).

Shown in Fig. C.2 are the KS test statistics of all combinations of the considered $E, P$ and $E_p$ datasets. It is at first important to note, that the KS test statistics are generally rather large for all combinations. However, similar to the results presented in Chapter 2 (and in particular in Fig. 2.2), but not as distinct, the highest uncertainty lies in the choice of the $E$ datasets. Further, reanalysis datasets again show highest inequalities with the Budyko framework. Regarding the different $P$ datasets, it is again the GPCP dataset showing highest similarity to the reference Budyko distribution. In general, the probabilistic evaluation supports the results presented in chapter 2.
Figure C.2: Probabilistic validation of hydrological dataset combinations (see Chapter 2 for more information) for the 1984-2005 period. Boxplots of all Kolmogorov–Smirnov test statistics related either to a) an individual $E$ or b) $P$ dataset and c) the $E_P$ estimates. Colors for the $E$ datasets denote the different classes (Mueller et al., 2011): LSMs with various forcings: green, LSMs from the TRENDY project (Sitch et al., 2013) (TR): blue, reanalysis: yellow. Percentage values to the right denote the average total number of points exceeding the physical water supply and demand limits. See text and Methods for more information.
Appendix to Chapter 5

D.1 Complete solution of the new formulation

Here we provide the complete solution of the new formulation introduced in Chapter 5. Equations 5.3, 5.5 and 5.7 form a system of differential equations. A necessary condition to solve this system is

\[
\frac{\partial f(x)}{\partial E_p} + \frac{\partial f(x)}{\partial E} \phi(y) = \frac{\partial \phi(y)}{\partial P} + \frac{\partial \phi(y)}{\partial E} f(x) \quad (D.1)
\]

Combining equation D.1 with equation 5.4 yields

\[
\frac{\partial f(x)}{\partial E_p} = \frac{\partial f(x)}{\partial E_p} \frac{\partial x}{\partial x} = \frac{1}{P} \left( 1 - \frac{\partial E}{\partial E_p} \right) \frac{\partial f(x)}{\partial x} = \frac{1}{P} (1 - \phi(y)) \frac{\partial f(x)}{\partial x} \quad (D.2a)
\]

\[
\frac{\partial f(x)}{\partial E} = \frac{\partial f(x)}{\partial E} \frac{\partial x}{\partial x} = \frac{1}{P} \left( \frac{\partial E_p}{\partial E} - 1 \right) \frac{\partial f(x)}{\partial x} = \frac{1}{P} \left( \frac{1}{\phi(y)} - 1 \right) \frac{\partial f(x)}{\partial x} \quad (D.2b)
\]

\[
\frac{\partial \phi(y)}{\partial P} = \frac{\partial \phi(y)}{\partial P} \frac{\partial y}{\partial y} = \frac{1}{E_p} \left( 1 - \frac{\partial E}{\partial P} \right) \frac{\partial \phi(y)}{\partial y} = \frac{1}{E_p} (1 - f(x)) \frac{\partial \phi(y)}{\partial y} \quad (D.2c)
\]
\[
\frac{\partial \phi(y)}{\partial E} = \frac{\partial \phi(y)}{\partial E} \frac{\partial y}{\partial E} = \frac{1}{E_p} \frac{\partial P}{\partial E} \left( \frac{1}{f(x) - 1} \right) \frac{\partial \phi(y)}{\partial y} = \frac{1}{E_p} \left( \frac{1}{f(x) - 1} \right) \frac{\partial \phi(y)}{\partial y}
\]

Substituting the factors in equation D.1 with those given in equations D.2 gives:

\[
\frac{\partial f(x)}{\partial x} \left( (1 - \phi(y)) + \left( \frac{1}{\phi(y)} - 1 \right) \phi(y) \right) = \frac{P}{E_p} \frac{\partial \phi(y)}{\partial y} \left( (1 - f(x)) + \left( \frac{1}{f(x)} - 1 \right) f(x) \right)
\]

\[
(1 - \phi(y)) \frac{\partial f(x)}{\partial x} = \frac{P}{E_p} (1 - f(x)) \frac{\partial \phi(y)}{\partial y}
\]

Expanding \( P/E_p \) yields under consideration of equations 5.4

\[
\frac{P}{E_p} = \frac{\frac{E_p + P - E}{E_p}}{\frac{E_p + P - E}{P}} = \frac{1 + \frac{P - E}{E_p}}{1 + \frac{E_p - E}{P}} = \frac{1 + y}{1 + x}
\]

From equation D.3 and equation D.4 follows

\[
(1 - \phi(y)) \frac{\partial f(x)}{\partial x} = \frac{1 + y}{1 + x} \left( 1 - f(x) \right) \frac{\partial \phi(y)}{\partial y}
\]

\[
\frac{1 + x}{1 - f(x)} \frac{\partial f(x)}{\partial x} = \frac{1 + y}{1 - \phi(y)} \frac{\partial \phi(y)}{\partial y}
\]

where each side is a function of \( x \) or \( y \) only. Assuming the result of each side is \( \alpha \) it follows

\[
\frac{1 + x}{1 - f(x)} \frac{\partial f(x)}{\partial x} = \alpha \quad \text{(D.6a)}
\]

\[
\frac{1 + y}{1 - \phi(y)} \frac{\partial \phi(y)}{\partial y} = \alpha \quad \text{(D.6b)}
\]

Integrating equation D.6a under consideration of the boundary condition given by equation 5.5 leads to the following expression for \( f(x) \)

\[
\int_0^x \frac{1}{1 - f(t)} \frac{\partial f(t)}{\partial t} \, dt = \alpha \int_0^x \frac{1}{1 - t} \, dt
\]

\[
[- \ln(1 - f(t))]_0^x = \alpha [\ln(1 + t)]_0^x
\]

\[
\ln(1 - f(x)) = -\alpha \ln(1 + x)
\]

\[
1 - f(x) = (1 + x)^{-\alpha}
\]

\[
f(x) = 1 - (1 + x)^{-\alpha}
\]
Integrating equation D.6b is different from the traditional solution given in Zhang et al. (2004), as we are using the new boundary condition given by equation 5.7

\[ \int_{y_0}^{y} \frac{1}{1 - \phi(t)} \frac{\partial \phi(t)}{\partial t} dt = \alpha \int_{y_0}^{y} \frac{1}{1 - t} dt \]

\[ [-\ln(1 - \phi(t))]_{y_0}^{y} = \alpha [\ln(1 + t)]_{y_0}^{y} \]

\[ \ln(1 - \phi(y)) - \ln(1 - \phi(y_0)) = \alpha (\ln(1 + y_0) - \ln(1 + y)) \]

\[ \ln(1 - \phi(y)) = \alpha \ln \left( \frac{1 + y_0}{1 + y} \right) \]

\[ 1 - \phi(y) = \left( \frac{1 + y_0}{1 + y} \right)^{\alpha} \]

\[ \phi(y) = 1 - \left( \frac{1 + y_0}{1 + y} \right)^{\alpha} \]  

\[ (D.8) \]

Considering the expansion from equation D.4 finally gives

\[ \frac{\partial E}{\partial P} = 1 - (1 + x)^{-\alpha} = 1 - \left( \frac{P}{E_p + P - E} \right)^{\alpha} \]  

\[ (D.9) \]

\[ \frac{\partial E}{\partial E_0} = 1 - (1 + y_0)^{\alpha} (1 + y)^{-\alpha} = 1 - (1 + y_0)^{\alpha} \left( \frac{E_0}{E_0 + P - E} \right)^{\alpha} \]

\[ (D.10) \]

In the next step, equation D.9 is integrated over \( P \). As equation D.9 is identical to those in Zhang et al. (2004), we follow their substitution approach. It follows

\[ E = E_0 + P - (k + P^{\alpha+1})^{\frac{1}{\alpha+1}} \]  

\[ (D.11) \]

where \( k \) is a function of \( E_0 \) only. Differentiate equation D.11 with respect to \( E_0 \) gives an estimate of \( \frac{\partial E}{\partial E_0} \), which used with equation D.10 determines \( k \)

\[ \frac{\partial E}{\partial E_0} = 1 - \frac{1}{\alpha + 1} (k + P^{\alpha+1})^{-\frac{\alpha}{\alpha+1}} \frac{\partial k}{\partial E_0} = 1 - (1 + y_0)^{\alpha} \left( \frac{E_0}{E_0 + P - E} \right)^{\alpha} \]

\[ (D.12) \]

This leads under consideration of equation D.11 to the following expression
\[
\frac{\partial k}{\partial E_0} = (\alpha + 1)(1 + y_0)^\alpha \left( \frac{E_0}{E_0 + P - E} \right)^\alpha (k + P^{\alpha + 1})^{\frac{\alpha}{1 + \alpha}} \\
= (\alpha + 1)(1 + y_0)^\alpha \left( \frac{E_0}{E_0 + P - (E_0 + P - (k + P^{\alpha + 1})^{\frac{1}{1 + \alpha}})} \right)^\alpha (k + P^{\alpha + 1})^{\frac{\alpha}{1 + \alpha}} \\
= (\alpha + 1)(1 + y_0)^\alpha E_0^\alpha \\
k = (\alpha + 1)(1 + y_0)^\alpha \int E_0^\alpha dE_0 \\
k = (1 + y_0)^\alpha E_0^{\alpha + 1} + C
\tag{D.13}
\]

with \(C\) being an integration constant. Substituting equation D.13 back into equation D.11, one obtains the following expression

\[
E = E_0 + P - ((1 + y_0)^\alpha E_0^{\alpha + 1} + C + P^{\alpha + 1})^{\frac{1}{1 + \alpha}}
\tag{D.14}
\]

and as \(\lim_{P \to 0} E = 0\) follows \(C = 0\). Substituting \(\kappa = \alpha + 1\) finally gives

\[
E = E_p + P - ((1 + y_0)^{\kappa - 1} E_p^\kappa + P^\kappa)^{\frac{1}{\kappa}}
\tag{D.15}
\]

### D.2 Derivative of \(F(\Phi, \kappa, y_0)\)

The derivative of the extended Budyko formulation \(F(\Phi, \kappa, y_0)\) given by equation 5.9 is obtained as follows:

\[
\frac{\partial F(\Phi, \kappa, y_0)}{\partial \Phi} = 1 - \Phi^{\kappa - 1} (1 + y_0)^{\kappa - 1} \left( \Phi^\kappa (1 + y_0)^{\kappa - 1} + 1 \right)^{\frac{1}{\kappa - 1}}
\tag{D.16}
\]

### D.3 Computing the actual slope

The actual slope \(m\) of the upper limit against which the obtained Budyko curve is converging to is smaller than \(-y_0\). We introduced equation 5.12 to calculate \(m\) and in the following we provide the complete solution in order to obtain equation 5.12.

The value of \(m\) is the slope of the linear function \(m\Phi + 1\) that forms the asymptote to \(F(\Phi, \kappa, y_0)\) given by equation 5.9. Hence,

\[
\lim_{\Phi \to \infty} [F(\Phi, \kappa, y_0) - (m\Phi + 1)] = 0.
\tag{D.17}
\]

Using equation 5.9 and dividing by \(\Phi\) yields

\[
\lim_{\Phi \to \infty} \left[ \frac{(1 + (1 + y_0)^{\kappa - 1} (\Phi^\kappa)^{\frac{1}{\kappa}}) \Phi + 1 - m}{\Phi} \right] = 0.
\tag{D.18}
\]
By raising the term in brackets to the power of $\kappa$ one obtains

$$\lim_{\Phi \to \infty} [(1 - m)^\kappa - \Phi^{-\kappa}(1 + \Phi^\kappa(1 + y_0)^{\kappa-1})] = 0, \quad (D.19)$$

and it follows

$$\lim_{\Phi \to \infty} [(1 - m)^\kappa - (1 + y_0)^{\kappa-1} - \Phi^{-\kappa}] = 0. \quad (D.20)$$

Since $\Phi^{-\kappa} \to 0$ for $\Phi \to \infty$ we obtain

$$(1 - m)^\kappa = (1 + y_0)^{\kappa-1}. \quad (D.21)$$

Solving for $m$ yields

$$m = (1 + y_0)^{1 - \frac{1}{\kappa}}. \quad (D.22)$$
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General Assembly of the European Geosciences Union, April 2013, Vienna, Austria. “Comprehensive evaluation of long-term hydrological data sets: Constraints of the Budyko framework.”