Doctoral Thesis

Solar absorption in the atmosphere
Improved estimates from surface and satellite observations

Author(s):
Hakuba, Maria Z.

Publication Date:
2015

Permanent Link:
https://doi.org/10.3929/ethz-a-010478709

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Solar absorption in the atmosphere – Improved estimates from surface and satellite observations

A thesis submitted to attain the degree of

DOCTOR OF SCIENCES of ETH ZURICH

(Dr. sc. ETH Zurich)

presented by

Maria Z. Hakuba
MSc ETH Environ. Sc, ETH Zurich
born August 3, 1984
citizen of Germany

accepted on the recommendation of

Prof. Dr. Martin Wild, examiner
Prof. Dr. Christoph Schär, co-examiner
Dr. Doris Folini, co-examiner
Dr. Gabriela Schaepman-Strub, co-examiner
Dr. Jörg Trentmann, co-examiner

2015
Abstract

The solar radiation absorbed by the Earth’s surface and the atmosphere is the primary source of energy driving the dynamical, hydrological, and thermal processes in our climate system. While knowledge on the solar energy exchange between Sun, Earth, and Space at the top-of-atmosphere (TOA) is well established through the recent availability of satellite measurements, the partitioning of the net solar flux between the surface and the atmosphere is still afflicted with large uncertainties, both in observations and climate models. Reasons for this arise mainly from the difficulty of directly measuring the distribution of solar energy within the climate system. On the one hand, the satellite retrieval of the surface and atmospheric fluxes, which requires radiative transfer modeling, is prone to uncertainties. On the other hand, direct observations at the ground lack sufficient spatial coverage to constrain the surface budget reliably. Thus, the TOA net solar flux at $240 \pm 2 \, \text{Wm}^{-2}$ is well constrained in the global mean, while the estimates of solar absorption at the surface and within the atmosphere vary in a range of more than $20 \, \text{Wm}^{-2}$, which corresponds to an uncertainty of 30% in atmospheric solar absorption.

In order to establish a key reference for the validation of climate model integrations and satellite retrieval, we make extensive use of direct measurements from both, space and surface, to quantify the present day (2000–2010) mean-state disposition of solar energy and associated uncertainties. Special emphasis we place upon the temporal and spatial quality assessment of the surface observations that represent the largest source of uncertainty in the solar absorption estimates. First, we objectively select ground-based surface solar radiation (SSR) records of sufficient temporal coverage and homogeneity as provided by the Baseline Surface Radiation Network (BSRN) and the Global Energy Balance Archive (GEBA), using four statistical tests to detect artifacts in a timeseries of likely non-climatic nature (Chapter 2). Secondly, we adjust the surface measurements to improve their spatial representativeness with respect to the gridded TOA irradiances (Chapters 3 and 4) provided by the Clouds and Earth’s Radiant Energy System (CERES) at $1^\circ$ spatial resolution. To quantify the surface and atmospheric column absorption over Europe, we then combine the temporally homogeneous and spatially representative SSR measurements with collocated satellite-derived surface albedo (MODIS) and TOA net solar flux (Chapter 5). Finally, we examine the associated cloud radiative forcing at the TOA, the surface, and in the atmosphere, thereby studying seasonal and spatial variations in atmospheric solar absorption and their underlying causes on the near-global scale (Chapter 6).

The spatial representativeness of a point measurement of surface solar radiation is a potential source of uncertainty in our approach of combining ground-based and gridded satellite data. Using a high-resolution ($0.03^\circ$) data product provided by the Satellite Application Facility on Climate Monitoring (CM SAF), we assess the small-scale variability in SSR and the spatial representativeness of 887 surface sites. We find absolute annual and monthly mean representation errors at these surface sites of on average 1–3% (3–5 Wm$^{-2}$) with respect to their $1^\circ$ surroundings and the fixed CERES grid that we correct for on a monthly mean basis.

Our best estimates of climatological annual mean surface and atmospheric solar absorption representative for Europe ($-9^\circ$ to $31^\circ$ East and $36^\circ$ to $64^\circ$ North) amount to $117.3 \pm 6 \, \text{Wm}^{-2}$.
(41.6 ±2% of TOA incident irradiance) and 65.0 ±3 Wm$^{-2}$ (23.0 ±1%), respectively. The fractional atmospheric absorption at 23% is thereby largely unaffected by variations in latitude and season and represents a useful quantity for the first-order validation of climate models.

The high temporal resolution (1-minute) and availability of both the total and diffuse SSR measurements at the BSRN sites, enables us to derive the clear-sky atmospheric solar absorption at 22 locations worldwide. We find that the presence of clouds enhances the atmospheric absorption by more than 10 Wm$^{-2}$ in the climatological annual mean. In line with this finding, the CERES products point to enhanced absorption by clouds as well, however the magnitude is a factor of three smaller due to a substantial overestimate in clear-sky atmospheric absorption.

To better understand the spatial robustness of fractional atmospheric solar absorption, we use the satellite-based CERES datasets to attribute spatial variations in atmospheric absorption on the near-global scale to spatial variations in the atmospheric composition, surface albedo, and cloud fraction, the key parameters in modulating the amount of solar energy absorbed by the atmosphere. Within the frame of this dataset, we see that clouds substantially add to the fairly uniform latitudinal distribution of atmospheric solar absorption (23%) under all-sky conditions.

The present thesis makes two significant contributions in the field of energy balance research. First, we improved the knowledge on the solar absorption partitioning under both all- and clear-sky conditions representative for Europe and beyond, which may serve as a reference for climate modeling and satellite retrieval. Secondly, we studied extensively the spatial representativeness of the surface-based solar radiation measurements, which is not only crucial in correcting for inherent collocation errors, but also for a wide range of other applications, such as the validation of gridded data products and the design of field campaigns. The study of both these scientific directions requires extension towards the full global scale and further analysis on spatial and temporal variations as well as their physical causes.
Zusammenfassung


Die räumliche Representanz der Punktmessungen von Solarstrahlung ist eine potentielle Fehlerquelle beim Kombinieren von Boden- und Satellitenmessungen. Mit Hilfe eines räumlich hoch aufgelösten Datensatzes (0.03°) der Satellite Application Facility on Climate Monitoring (CM SAF), studieren wir die kleinskalige Variabilität in der Bodenstrahlung und die räumliche Representanz von 887 Bodenstationen. Die absoluten jährlichen und monatlichen Abweichun-
gen an diesen Stationen gegenüber ihrer $1^\circ$ Umgebungen und dem CERES Gitter belaufen sich auf $1–3\%$ ($3–5 \text{ Wm}^{-2}$) und werden auf monatlicher Basis korrigiert.

Für die Oberflächen- und Atmosphärenabsorption über Europa (-9°-31° Ost, 36°-64° Nord) ergeben sich folgende klimatologische Mittelwerte: $117.3 \pm 6 \text{ Wm}^{-2}$ ($41.6 \pm 2\%$ der ODA Einstrahlung) und $65.0 \pm 3 \text{ Wm}^{-2}$ ($23.0 \pm 1\%$). Die normalisierte Atmosphärenabsorption von etwa $23\%$ schwankt dabei nur minimal in Abhängigkeit von geografischer Breite und Jahreszeit und stellt eine brauchbare Größe für die approximative Validierung von Klimamodellen dar.

Dank der hohen zeitlichen Auflösung der an den BSRN Stationen gemessenen totalen und diffusen Solarstrahlung, können wir die Atmosphärenabsorption unter wolkenfreien Verhältnissen an 22 Orten weltweit bestimmen. Es stellt sich heraus, dass Wolken zu einer Erhöhung der Atmosphärenabsorption von mehr als $10 \text{ Wm}^{-2}$ führen. Auch das CERES Produkt weist auf einen positiven Wolkeneffekt hin, dieser ist jedoch um einen Faktor drei reduziert.

Um die räumliche Robustheit der normalisierten Atmosphärenabsorption besser zu verstehen, nutzen wir das satelliten-basierte CERES Produkt, um räumliche Variationen in der Atmosphärenabsorption auf räumliche Variationen in der Komposition der Atmosphäre, Bodenreflektanz und Bewölkung zurückzuführen. Diese Variablen beeinflussten massgeblich die Menge der absorbierten Solarstrahlung in der Atmosphäre. Innerhalb dieses Datensatzes sehen wir, dass Wolken einen grossen Einfluss auf die konstante ($23.0 \pm 1\%$) zonale Verteilung der Atmosphärenabsorption haben.

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Chapter 1

Introduction

“The sun, with all those planets revolving around it and dependent on it, can still ripen a bunch of grapes as if it had nothing else in the universe to do.”

Galileo Galilei

1.1 Motivation

The Earth’s energy balance represents the principal framework within which scientists proceed to comprehend and study the planet’s climate system. The solar radiation absorbed by the climate system, at the surface and in the atmosphere, is thereby the ultimate source of energy, controlling most pivotal processes such as the hydrological cycle, atmospheric motions, plant productivity, and the thermal conditions that facilitate life on Earth in its present form. Currently, profound knowledge on the incoming and outgoing solar fluxes at the top-of-atmosphere (TOA) is well established through space-born programs such as the Clouds and Earth’s Radiant Energy System (CERES, [Wielicki et al., 1996; Loeb et al., 2009]). This enables us to quantify the total solar energy absorbed by the climate system with high accuracy. However, global estimates of surface and atmospheric solar absorption still lack confidence, since satellite instruments do not measure these fluxes directly and require radiative transfer modeling in their retrieval [e.g., Pinker et al., 1995]. Direct observations of surface solar radiation (SSR) and surface albedo to compute the net solar flux at the surface exist, but their limited spatial coverage represents a major constraint in accurately determining a global mean [e.g., Ohmura and Gilgen, 1993]. Consequently, observational estimates of solar absorption at the surface and within the atmosphere feature a large spread, varying in a range of more than 20 W m\(^{-2}\), which corresponds to an uncertainty of 30% in atmospheric absorption [e.g., Budyko, 1982; Li et al., 1997; Hatzianastassiou et al., 2005; Trenberth et al., 2009; Wild et al., 2013].

Missing a reliable reference, global climate model (GCM) integrations do not attain consistent estimates either. Although tuned at TOA to be consistent with latest satellite measurements, the surface and atmospheric absorption as reproduced by the latest generation of IPCC/CMIP5 models range within 10 W m\(^{-2}\) (13%) [Wild et al., 2013]. Nevertheless, they show signs of improvement against the CMIP3 generation, producing a range of 15 W m\(^{-2}\) (20%) [Wild et al., 2005, 2008]. Still, common to many GCMs, their excessive surface solar radiation estimates are indicative for an underestimate in atmospheric solar absorption, which ultimately affects the simulated dynamical and hydrological conditions [Wild et al., 1998, 2008, 2013].

A heated debate in the 1990’s/early 2000’s on whether or not this underestimate arose from – observed but not modeled – “anomalous” cloud absorption, came to the conclusion that the

1
model treatment of clear-sky absorption rather than that of cloud absorption had to be the cause
[Stephens and Tsay, 1990; Cess et al., 1995; Li et al., 1995; Arking, 1996; Stephens et al., 1996; Wild and Ohmura, 1999; Li, 2004]. However still today, the precise magnitude of cloud absorption, which strongly depends on the cloud type and prevalent atmospheric conditions, represents an unknown in current energy balance research.

The present thesis aims at deriving improved estimates of present day (2000–2010) mean-state surface and atmospheric solar absorption through combining direct surface and collocated satellite measurements to provide a reference for climate model integrations and satellite retrieval. Focusing on Europe, we thereby put particular attention on the quality assessment of the datasets used. A major issue is the spatial representativeness of the surface observations with respect to the gridded satellite products and we expend two Chapters to thoroughly study potential collocation errors that might at least partially explain the large spread and biases in previous estimates of atmospheric solar absorption [Li and Trishchenko, 2001]. Beyond the application presented here, information on the spatial representativeness of the point observations is essential as they are often used to validate gridded datasets, such as climate model output and satellite products. Deviations between these gridded products and the point observations may not only be caused by uncertainties in retrieval and parametrization, but also by a possible lack of spatial representativeness of the surface measurements [e.g., Li et al., 2005].

We furthermore estimate surface solar radiation under cloud-free conditions at a number of surface sites distributed worldwide, which enables us to study the magnitude of the cloud radiative forcing on atmospheric absorption. To better understand and attribute spatial variations in atmospheric solar absorption and atmospheric cloud radiative forcing on the near-global scale, we investigate the role of clouds within the frame of a satellite-derived data product providing the TOA, surface, and atmospheric solar fluxes under both all- and clear-sky conditions.

In the following, we briefly describe the theoretical background on solar absorption in the atmosphere and at the surface, and present our main objectives and outline of this thesis.

1.2 A quick tour: Absorption of solar radiation

The depiction of the global energy balance and the quantification of its radiative components have a long history reaching back to the early 20th century. Ever since, these estimates have been revised through the use of more complete and comprehensive datasets and methods including climate modeling and satellite retrieval. Figure 1.1 presents a compilation of nine energy balance schematics including the TOA, surface, and within atmosphere budgets [Abbot and Fowle, 1908; Dines, 1917; London, 1957; Ramanathan, 1987; Kiehl and Trenberth, 1997; Ohmura and Raschke, 2005; Trenberth et al., 2009; Stephens et al., 2012; Wild et al., 2013]. Early representations of the global energy balance were based on data obtained at a single or few ground observatories [Abbot and Fowle, 1908], mathematical considerations [Dines, 1917], and simple radiative transfer modeling [London, 1957]. The onset of the satellite-era provided improved data coverage and consistent TOA fluxes. Hence, when comparing the remaining schematics [e.g., Trenberth et al., 2009; Stephens et al., 2012; Wild et al., 2013], the TOA balances are in quite good agreement with a net solar flux of around $240 \pm 2$ W m$^{-2}$, while some of the largest discrepancies are found in the surface fluxes and atmospheric solar absorption, the latter ranging between $67$ W m$^{-2}$ [Kiehl and Trenberth, 1997] and $96$ W m$^{-2}$ [Ohmura and Raschke, 2005]. The surface and atmospheric fluxes are thereby based on either GCM simulations [e.g., Ramanathan, 1987; Wild et al., 2013] or satellite retrieval [e.g., Trenberth et al., 2009; Stephens et al., 2012], constrained or validated with ground-based observations.
Figure 1.1: Global energy balance schematics and radiative flux estimates by Abbot and Fowle [1908]; Dines [1917]; London [1957]; Ramanathan [1987]; Kiehl and Trenberth [1997]; Ohmura and Raschke [2005]; Trenberth et al. [2009]; Stephens et al. [2012]; Wild et al. [2013]. Units are W m$^{-2}$ unless otherwise indicated.

of the surface budgets. The majority of state-of-the-art GCMs tend to overestimate the surface solar radiation flux as compared to ground observations, which points to an underestimate in atmospheric absorption [Wild et al., 1995, 2008, 2013]. This kind of partitioning in return, may lead to an accelerated hydrological cycle and intensified atmospheric flow in some GCM simulations [e.g., Zhang et al., 1998; Kiehl et al., 1995; Liu, 2003].

1.2.1 Solar absorption in the atmosphere

Through scattering and absorption processes, the atmosphere controls the amount of incoming shortwave solar radiation (0.2–5 µm) that reaches the ground and the amount of solar radiation that escapes to space. Under the assumption of direct irradiance under cloud-free conditions, the transmittance of the atmosphere $T_\lambda$ at a specific wavelength $\lambda$ can be described by the Beer-Lambert Law (equation 1.1), defining it as the ratio of transmitted radiation intensity after having passed a medium such as the atmosphere $I_\lambda,1$ and the incident radiation at the top-of-atmosphere $I_\lambda,0$. Following Beer’s Law, the transmittance decays exponentially as a function of the atmospheric optical thickness $\tau_\lambda$ and the extinction path $ds$ of the solar beam (Figure 1.2, left). The latter is a function of the solar zenith angle $\theta$. Hence, the absorbance of the atmosphere at a certain point in time and space strongly depends on latitude and season. The optical thickness $\tau_\lambda$ is the product of the absorption coefficient $\epsilon$, assuming a non-scattering atmosphere, and the vertical path length $dz$ (equation 1.2), which is furthermore controlled by surface elevation. Its relation to the slant extinction path $ds$ is depicted in Figure 1.2 (left).
The total absorption coefficient equals the sum of the absorption coefficients of the individual atmospheric components, such as gas molecules and aerosols.

\[
T_\lambda = \frac{I_{\lambda,1}}{I_{\lambda,0}} = e^{-\tau_\lambda} 
\]

(1.1)

\[
\tau_\lambda = \epsilon_\lambda dz, \quad \text{with } dz = -\cos(\theta)ds
\]

(1.2)

Through electron excitation, the atmospheric gases absorb solar shortwave radiation at specific wavelengths, e.g., ozone and oxygen absorb predominantly in the UV, and water vapor in the near-IR. Figure 1.2 (right), adapted from Houghton [1977], shows the black body functions of Sun and Earth (a) and the spectrally resolved absorption by a vertical column of atmosphere (b). The gases responsible for the main absorption features are indicated at the corresponding wavelength of incident energy from the sun or terrestrial emissions, respectively.

Under all-sky conditions, clouds play a major role in modulating the radiative balance at the TOA and at the surface. Their impact on atmospheric absorption was heavily debated during the 1990’s and early 2000’s. Several studies found “anomalous” cloud absorption of up to 30 Wm$^{-2}$ based on observational evidence [e.g., Cess et al., 1995; Pilewskie and Valero, 1995; Arking, 1996] and used this feature to explain biases in GCM simulations. However, various other studies opposed these findings [e.g., Stephens and Tsay, 1990; Li et al., 1995; Li, 2004; Wild and Ohmura, 1999; Ramanathan et al., 1989; Ackerman et al., 2003] and found that clouds, depending on their vertical location and optical properties, contribute at most a third of the earlier estimates to atmospheric solar absorption. Still today, climate models tend to underestimate atmospheric solar absorption [Wild et al., 2013]. However, the potentially poor representation of solar absorption in the cloud-free atmosphere is of at least equal concern as the role of clouds.

**Absorption by water vapor**

Representing the most potent absorber of shortwave radiation in the near-IR, it is worth discussing the role of water vapor in more detail. Most of the absorption through water vapor
occurs in the lower troposphere, which leads to rather negligible heating rates than what is observed in the cooler stratosphere due to UV absorption by ozone \cite{Yamamoto and Onishi, 1952}. Nevertheless, its contribution to the total shortwave absorption is three times larger than that of ozone \cite{Hartmann, 1994; Kiehl and Trenberth, 1997}, with around 70\% under cloud-free conditions. Following Beer’s law, the relationship between the absorbance of the atmosphere, defined as the negative natural logarithm of the transmittance, and the optical thickness $\tau$ would be linear. However, this relationship holds only for very low absorber concentrations. Various studies \cite[e.g.,][]{Yamamoto and Onishi, 1952; McDonald, 1960; Solomon et al., 1998; Tarasova and Fomin, 2000; Paynter and Ramaswamy, 2011} have extensively measured, modeled, and described water vapor absorption and its spectral dependencies. Figure 1.3 shows curves of absorptivity ($a$) versus precipitable water vapor ($u$) from early studies before 1960 (left) and recent simulations \cite{Paynter and Ramaswamy, 2012} (bottom, right). McDonald \cite{1960} found that these empirical exponential fits could be approximated by a linear relationship between $a$ and $u^{0.3}$ presented in Figure 1.3 (top, right). Still today, water vapor absorption is a vital topic in climate research. Climate models often tend to overestimate the solar radiation received at the ground under clear-sky conditions, which has been partly attributed to an underestimate of atmospheric absorption in the near-IR region \cite[e.g.,][]{Kato et al., 1997; Kinne et al., 1998; Tarasova and Fomin, 2000; Wild and Ohmura, 1999; Wild, 2000; Kim and Ramanathan, 2012}. For example, Paynter and Ramaswamy \cite[2012, 2014] showed that the inclusion of the shortwave water vapor continuum into GCMs enhances the clear-sky absorption by 1 to 3 Wm$^{-2}$. Another potential source of error in the modeled atmospheric absorption estimates arises from the representation of (absorbing) aerosols, which is discussed in more detail below.

**Figure 1.3:** Left: Absorption of solar radiation $a$ versus precipitable water vapor $u$ from various studies before 1960. Top right: Absorption of solar radiation $a$ versus precipitable water vapor $u^{0.3}$. Adapted from McDonald \cite{1960}. Bottom right: Absorption of solar radiation versus water vapor as simulated by Paynter and Ramaswamy \cite{2012}.
Overall, the direct radiative forcing across all aerosol types is negative at the TOA with around \(-0.5 \pm 0.4\) Wm\(^{-2}\) and governed by the aerosol particles’ ability to scatter and absorb solar radiation [Boucher et al., 2013; Myhre et al., 2013]. Besides natural compounds of dust or sea salt, aerosol particles may contain chemical species of anthropogenic origin, such as sulfates, organics, and black carbon (BC), which mostly originate from biomass burning and fossil fuel combustion [Haywood and Boucher, 2000]. Pure sulfate aerosols primarily scatter solar radiation and yield an increase in reflected solar flux at the TOA, which is nearly identical to the reduction in solar radiation at the surface [Charlson et al., 1991]. Carbonaceous aerosols, such as BC, primarily absorb solar radiation in the atmosphere [Grassl, 1975], which substantially reduces the solar radiation at the surface and the solar radiation reflected to space [Hansen et al., 1997; Satheesh and Ramanathan, 2000]. Hence at the TOA, the direct BC effect opposes the cooling effect of sulfates and organics, while at the surface, all aerosols reduce solar radiation.

According to Ramanathan et al. [2001] and Ramanathan and Carmichael [2008] black carbon is the dominant absorber of solar radiation in the visible bands and represents the second strongest contributor to global warming with as much as 55% of the contribution by CO\(_2\). Figure 1.4 (left), adapted from Ramanathan and Carmichael [2008], compares the TOA, atmospheric, and surface radiative forcing of different atmospheric constituents, such as greenhouse gases (a), CO\(_2\) (b), BC (c), and non-BC aerosols (d). The overall positive BC forcing at TOA composes from three pathways: (1) absorption of solar radiation in the atmosphere, (2) reduction of surface albedo via soot deposition, (3) reduction of cloud albedo through enhanced absorption by droplets and ice crystals. Present global estimates suggest an atmospheric heating due to BC solar absorption (1) of around 2.6 Wm\(^{-2}\), which is almost double the heating due to greenhouse gases. However, the BC absorption of solar radiation leads to a surface dimming at the same time, hence to a redistribution of solar energy rather than a TOA forcing, which has substantial impact on the radiative-convective coupling of the atmosphere and the latent heat flux. Unlike the atmospheric gases, due to its very limited atmospheric lifetime, BC is locally more concentrated to its major source regions in the tropics and East Asia (Figure 1.4, right). There, it enhances the solar heating in the lower atmosphere by as much as 16 Wm\(^{-2}\) (∼20%).
Absorption by clouds

Whether and by how much the atmospheric column absorption of solar radiation is enhanced due to the presence of clouds depends on various factors, such as the cloud type itself, the surface albedo, and the composition of the background atmosphere [e.g., Stephens and Tsay, 1990]. Clouds impact the atmospheric solar absorption through mainly three pathways [e.g., Raschke et al., 2005; Crisp, 1997]: (1) As clouds reflect large amounts of solar radiation back to space and transmit comparably small amounts to the ground, they reduce considerably the absorption by water vapor below the clouds. (2) Cloud droplets and the water vapor within the cloud absorb more sunlight than just the water vapor in their layers alone. (3) Some of the reflected sunlight is absorbed on its second passage through the water vapor column above the cloud [Lacis and Hansen, 1974] and the ozone layer in the stratosphere; an effect that is comparably small and presumably more pronounced over dark surfaces. The specific absorption by the cloud depends on its thickness and optical properties, i.e., a single cloud droplet absorbs very small amounts of incoming solar radiation (0.1%), but through multiple scattering processes within the cloud, the absorption by the droplets and cloud water content multiplies a hundredfold [Stephens and Tsay, 1990]. Hence, depending on the cloud’s vertical location, thickness, and optical depth [Ramaswamy and Freidenreich, 1998], its specific absorption (2) can offset or even overcompensate the reduced pathlength effect (1).

Commonly, the cloud radiative forcing (CRF) is defined as the difference between the radiation fluxes under all-sky and clear-sky conditions [e.g., Harrison et al., 1990]. Using estimates of the CRF on surface solar absorption (ASRsurf) and TOA net solar flux (TOAnet), the magnitude of cloud absorption is often quantified through the forcing ratio $R$ (equation 1.3) [Li et al., 1995]. Taking this ratio of the cloud forcing at the surface ($\text{CRF}_{\text{surf}}$) to the forcing at the TOA ($\text{CRF}_{\text{TOA}}$) accounts for differing clear-sky frequencies to facilitate comparability across different climate regimes.

$$R = \frac{\text{CRF}_{\text{surf}}}{\text{CRF}_{\text{TOA}}} \quad \text{with}$$

$$\text{CRF}_{\text{surf}} = \text{ASR}_{\text{surf all}} - \text{ASR}_{\text{surf clear}}$$

$$\text{CRF}_{\text{TOA}} = \text{TOA}_{\text{net all}} - \text{TOA}_{\text{net clear}}$$

The magnitude of cloud absorption depends strongly on the definition of the CRF, which might have caused discrepancies between earlier studies [Sohn and Robertson, 1993; Li and Trishchenko, 2001; Erlick and Ramaswamy, 2003]. While Sohn and Smith [1992] define the CRF as the radiation change by clouds during the transition from the cloudy state to the cloud-free state with surface and atmospheric variables held constant, the CRF definition by, e.g. Ramanathan et al. [1989] and many others, implicitly includes additional radiative effects due to variations of atmospheric variables associated with the change in cloud cover. According to the latter definition, the “cloud forcing on atmospheric solar absorption” as derived in the present thesis (Chapter 6) does not exclusively represent the specific impact by clouds, but the absorption by the cloudy atmosphere including the changes in atmospheric background conditions as compared to a measured or derived clear-sky scene. Evidently, the widely accepted term “cloud absorption”, as occasionally used in this thesis and many earlier studies, is somewhat misleading and prone to definition and uncertainty issues. Likely, these issues caused, at least partially, the debate on the magnitude of cloud absorption [Li and Trishchenko, 2001].
1.2.2 Solar absorption at the surface

In order to maintain radiative balance, the net energy absorbed at the surface has to be released in the form of latent heat, sensible heat, and the emission of thermal radiation. Consequently, the surface absorption of solar radiation plays an essential role in driving the hydrological, dynamical, and thermal conditions of the climate system [Kiehl and Trenberth, 1997]. To realistically simulate the Earth’s climate, it is hence crucial to attain an accurate partitioning of the solar energy absorption between the surface and the atmosphere [Liu, 2003].

Representing a secondary quantity, the surface absorption itself cannot be directly measured, but is determined by multiplying the downwelling surface solar radiation with the surface co-albedo \((1 - \text{albedo})\) [Hansen et al., 2000]. Hence, uncertainties in both these quantities affect the estimate of surface absorption and ultimately the estimate of atmospheric solar absorption, which we derive as the residual between the net solar flux at the TOA and the surface absorbed solar radiation. The main sources of uncertainty arise from the incapability of directly measuring the surface fluxes using remote techniques [e.g., Pinker et al., 1995], the scarce spatial coverage by direct observations at the ground [Ohmura and Gilgen, 1993], the operational accuracy of the measurements themselves [e.g., Michalsky et al., 1999], and the spatial representativeness of the point-scale observations [e.g., Li et al., 2005; Roman et al., 2009] that we briefly introduce below.

Surface albedo

The surface albedo, defined as the ratio of upwelling to downwelling solar radiation, ultimately controls the amount of solar energy that is absorbed by the oceans and the land. In contrast to the downwelling surface solar radiation, the upwelling fluxes are rarely measured and archived [Ohmura and Gilgen, 1993], which aggravates the estimation of surface albedo from direct ground-based observations. Hence, in this thesis we use satellite-based estimates of surface albedo in combination with direct ground observations of downwelling solar radiation to compute the surface absorption. The satellite data do not only provide more complete spatial coverage, but also help to bypass spatial-scale disparities when combining the different datasets. In this thesis, we make extensive use of the satellite-derived land surface albedo product provided by the Moderate Resolution Imaging Spectroradiometer (MODIS) [Schaaf et al., 2002] on the Terra and Aqua platforms. The MODIS products provide estimates of the intrinsic white-sky (bihemispherical, [Lucht et al., 2000; Schaepman-Strub et al., 2006]) and black-sky (directional hemispherical, at mean solar local noon) albedos. Under both direct beam and diffuse skylight, the actual (blue-sky) albedo at a given solar zenith angle can be approximated by a linear weighted combination of the white-sky and black-sky albedos [Lewis and Barnsley, 1994], corresponding to the actual ratio of diffuse to direct illumination.

Due to several constraints, the derivation of blue-sky albedo at the observational sites measuring downwelling SSR considered here, is not straightforward and we decided to rely on the intrinsic white-sky albedo. In contrast to the black-sky albedo, the white-sky albedo is independent of viewing and solar angles and, hence, comparable spatially and temporally [Gao et al., 2005]. Under most atmospheric conditions, the white-sky and black-sky albedos bracket the blue-sky albedo [Stroeve et al., 2005], and the difference between these quantities is rather small as compared to actual product uncertainties [Schaepman-Strub et al., 2006]. We present more details on the product and its accuracy in Chapter 5.
1.3 Objectives and outline

The overarching goal of this thesis is to quantify the present day (2000–2010) mean-state disposition of solar energy within the climate system and associated uncertainties to provide a reference for climate modeling and satellite retrieval. Following Figure 1.5 (adapted from Chapter 5), we combine ground-based measurements of surface solar radiation (SSR) with satellite-derived surface albedo and TOA net solar flux to obtain best-we-can estimates of surface and atmospheric solar absorption representative for Europe and beyond. The key prerequisite is thereby the quality assessment of the ground-based solar radiation measurements. In detail, this concerns especially the issue of spatial representativeness, which arises from our methodology of combining point-scale measurements with gridded datasets. Likewise important is the temporal quality of the ground-based SSR records, which we evaluate using absolute homogeneity tests, tools that represent an objective way to select data series of sufficient quality. Of further particular significance is the evaluation of cloud radiative effects and their magnitude, as well as their role in modulating the spatial pattern of atmospheric solar absorption.

In brief, the main objectives we seek to accomplish are to:

1) Identify ground-based surface solar radiation measurements of high quality and adjust them to improve their spatial representativeness.
Figure 1.5: Fundamental objective: Combination of satellite-derived top-of-atmosphere net solar flux and surface albedo (area averages) with ground-based observations of surface solar radiation (point measurements) to estimate surface and atmospheric solar absorption. See Chapter 5 for further details. Note: CERES defines the TOA at 20 km above the surface [Loeb et al., 2002].

2) Provide improved estimates of mean-state surface and atmospheric solar absorption and quantify associated uncertainties.

3) Quantify atmospheric cloud radiative effects and examine spatial variations in atmospheric solar absorption under clear-sky and all-sky conditions.

To address these objectives, we organized this thesis in seven Chapters. Four peer-reviewed publications (Chapters 2 to 5) and one article in preparation (Chapter 6) are presented in the form of self-contained scientific contributions. Chapter 7 redraws their main conclusions, limitations, and options for future research. In the following, we briefly outline the scientific Chapters’ contents:

Chapter 2 [Hakuba et al., 2013a] exemplifies the application of four absolute homogeneity tests to identify surface solar radiation series of sufficient quality for trend analysis over Europe and the computation of climatologies to derive surface and atmospheric absorption.

Chapters 3 and 4 [Hakuba et al., 2013b & Hakuba et al., 2014b] analyze the spatial small-scale variability in surface solar radiation and the spatial representativeness of 887 surface sites with respect to surroundings of variable size. The derived site-specific representation errors are used to improve the spatial representativeness of the observational records prior to their combination with the gridded satellite products to obtain surface and atmospheric absorption.

Chapter 5 [Hakuba et al., 2014b] quantifies mean-state (2000–2010) surface and atmospheric solar absorption based on high-quality datasets over Europe, illustrates spatial and seasonal variations, and extensively discusses the sources and magnitude of uncertainties.
Chapter 6 [Hakuba et al., in preparation] estimates cloud radiative effects from both, the ground and satellite perspectives, and attributes spatial variations in atmospheric solar absorption to spatial variations in cloud cover and other climatic variables on the near-global scale.
Chapter 2

Testing the Homogeneity of Short-Term Surface Solar Radiation Series in Europe
Testing the Homogeneity of Short-Term Surface Solar Radiation Series in Europe*

Maria Z. Hakuba¹, Doris Folini¹, Arturo Sanchez-Lorenzo¹, Martin Wild¹

Abstract

Non-climatic factors, such as changes in instruments or the relocation of meteorological stations, can cause sudden shifts or gradual biases in a climate data time series. The use of such inhomogeneous time series in data analysis might lead to false conclusions about climate variability and change. In this work, we test the homogeneity of 172 surface solar radiation (SSR) monthly series over Europe available in the Global Energy Balance Archive (GEBA) during the period 2000–2007. Four absolute homogeneity tests are applied to each series, and a classification of inhomogeneous and homogeneous stations is given. The results show that 20 out of 172 series (11.6% of the total) are inhomogeneous at the 99% significance level. The mean average time series of both data sets, the original and the one with only the homogeneous series, show positive linear trends (0.59 and 0.70 Wm⁻² yr⁻¹). The omission of the inhomogeneous series increases the original trend by 0.11 Wm⁻² yr⁻¹ or 1.1 Wm⁻² decade⁻¹. Our results highlight the importance of testing the homogeneity of SSR time series before any trend analysis is performed.


¹Institute for Atmospheric and Climate Science, ETH Zurich, Switzerland
2.1 Introduction

Ground-based surface solar radiation (SSR) measurements are of utmost importance for the study of climatic changes and the validation of climate model simulations and remote sensing data. As has been pointed out recently [Wild, 2011], historic radiation data are of variable quality and may require homogenization. Observational data quality relies to a large extent on the instruments used, their maintenance and calibration, as well as the station environment. Changes in these non-climatic factors may superimpose non-climatic variations and sharp inhomogeneities in the time series. The use of such afflicted time series in trend analysis and model validation might lead to false conclusions. In this study, we apply absolute homogeneity tests to European radiation records from the Global Energy Balance Archive (GEBA, [Gilgen and Ohmura, 1999]) to identify inhomogeneous time series that would either have to be homogenized or neglected from further analysis. Numerous statistical tests have been developed to test monthly-resolution time series on non-climatic jumps [Peterson et al., 1998]. We follow closely the approach used by the European Climate Assessment and Dataset (ECA&D) that applies four absolute tests to check the homogeneity of different meteorological variables [e.g., Wijngaard et al., 2003]. The main objective of the present study is to test the homogeneity of short-term SSR records (2000–2007) over Europe, the continent with the highest density of data in the GEBA, and to verify the performance of the absolute methods used here. It is noteworthy to highlight that there is a lack of SSR series in the major part of the world, which prevents the use of relative methods to test the homogeneity of time series in these areas. The results presented here form part of a larger project that aims at deriving the partitioning of solar absorption at a global scale through the combination of ground-based surface solar radiation data with recently available satellite products. Continuous monitoring of the Earth radiation budget by satellites only became operational around the year 2000, therefore the homogeneity testing focuses on the associated ground-based data available since 2000.

2.2 Data and Methods

The Global Energy Balance Archive (GEBA, [Gilgen and Ohmura, 1999; Ohmura and Gilgen, 1993]), maintained at the Institute for Atmospheric and Climate Science (IAC) at ETH Zurich, is a database for worldwide measurements of radiation fluxes, predominantly SSR measure-

Figure 2.1: Time series of monthly anomalies from Ciudad Real, Spain (a), indicated to be inhomogeneous by all four tests; and Lindenberg, Germany (b), homogeneous.
2.3 RESULTS

Figure 2.2: Number of positive tests per test type in blue. Number of contributions to inhomogeneous (3–4 positive tests) time series in black contours.

ments. The archive contains more than 2'000 stations with more than 450'000 monthly mean values. Many records date back to the 1960s. For this study, we use the SSR series available over Europe after 2000. To address the temporal homogeneity of GEBA records, we follow the approach used by the ECA&D [Wijngaard et al., 2003], which uses three absolute single change-point homogeneity tests and one test for randomness to detect inhomogeneous time series; i.e. the Standard Normal Homogeneity test (SNHT) [Alexandersson, 1986], the Pettitt test [Pettitt, 1979], the Buishand range test [Buishand, 1981], and the Von Neumann ratio test [Von Neumann, 1941]. They define a time series to be afflicted with an inhomogeneity if at least three out of these four tests indicate a sudden shift in the mean or change in variance. Specifically, the SNHT, Buishand, and Pettitt tests proceed under the null-hypothesis that the individual data points are independent and identically distributed; alternatively the tests suppose a step-wise shift in the mean of the time series. The Von Neumann ratio test indicates whether the sample variance inflates over time. The three aforementioned location-specific tests differ and complement each other: SNHT and Buishand tests are parametric tests and assume a normal distribution of the mean values, Pettitt test is non-parametric and based on the values’ ranks, thus, makes no assumption about the distribution. Equally, the SNHT test identifies breaks particularly at the beginning and the end of the time series, Buishand and Pettitt are particularly sensitive to breaks in the middle of the time series. Here, the tests are applied to deseasonalized monthly anomalies over the period 2000–2007.

2.3 Results

Before applying the homogeneity tests, we remove monthly values that are flagged to be erroneous by the quality control as implemented in the GEBA [Gilgen and Ohmura, 1999]. From totally 269 European GEBA stations with monthly mean data available between 2000 and 2007, 205 cover at least five years, 172 of them with less than 30% data gaps and at least one complete annual cycle. Moreover, 80% of them have data up to 2007. We tested these 172 series of deseasonalized monthly anomalies based on the approach explained above and found 20 series (11.6%) to be inhomogeneous at the 99% significance level (3–4 positive tests). In Figure 2.1
(a) we give the example of an inhomogeneous time series measured at Ciudad Real (Spain). All tests indicate a stepwise shift in the mean around 2006, which fits well to the obvious negative drift starting in 2005/2006. Figure 2.1 (b) shows a homogeneous time series at Lindenberg (Germany), where none of the tests indicates a shift in the mean or change in variance. Of all tests, the Pettitt test is the most sensitive, indicating 39 breaks in total and contributing to all 20 inhomogeneous (3–4 positive tests) time series (see Figure 2.2). Least sensitive is the Von Neumann ratio test with 21 hits, and only 11 contributions.

In total, 7 SSR series are indicated to be inhomogeneous by all four tests, 13 by three tests (which amounts to 20 series flagged as inhomogeneous), and 11 by two tests, to be flagged as doubtful following the ECA&D recommendations [Wijngaard et al., 2003]. 21 time series are found to be inhomogeneous by only one test. For 120 series, none of the tests gives positive proof of an inhomogeneity.

Most of the 20 inhomogeneous SSR series (Figure 2.3, asterisks) are located in Switzerland (5), Spain (4), and the Balkans (5). Furthermore, 6 (14) of them show a decreasing (increasing) trend in SSR (Figure 3, blue circles for negative trends, yellow squares for positive trends). We applied linear regression to the mean average time series of both sub sets (Figure 2.4); i.e. using the original 172 and 152 homogeneous series. Both the original and homogenous mean time series show positive trends of 0.59 (p-value: 0.06) and 0.70 Wm$^{-2}$yr$^{-1}$ (p-value: 0.02), respectively. Although the majority of inhomogeneous series have positive trends (70%), their omission enhances the observed increase in solar radiation by 0.11 Wm$^{-2}$yr$^{-1}$ or 1.1 Wm$^{-2}$decade$^{-1}$. The positive trends indicate a “brightening” in SSR over Europe, in line with previous studies [Wild, 2011; Wild et al., 2005, 2009].
2.4 Conclusions

We applied four absolute single change-point homogeneity tests to 172 European SSR series (deseasonalized monthly anomalies) over the period 2000–2007 and found 20 (11.6%) of them to be inhomogeneous at the 99% significance level. The use of multiple tests is recommended, as they make different assumptions and vary in sensitivity. Most of the 20 inhomogeneous stations are located in Switzerland, Spain, and the Balkans. Linear regression has been applied to the mean average time series of both the original and the homogeneous subset. The overall variability is not affected substantially by the omission of the 20 inhomogeneous series, however, the positive annual trend of 0.59 Wm$^{-2}$yr$^{-1}$ is enhanced by 0.11 Wm$^{-2}$yr$^{-1}$ or 1.1 Wm$^{-2}$decade$^{-1}$ after excluding the inhomogeneous series. These results point out that the inclusion of inhomogeneous time series in trend analysis may introduce substantial errors that lead to false conclusions about SSR variability. Using inhomogeneous data for model validation purposes might as well lead to misinterpretation of model performance due to unphysical biases. We recommend careful quality control and homogeneity testing of SSR time series in the GEBA in order to study merely climatic (free of non-climatic factors) variability and changes in solar radiation.

Acknowledgments

This work was financially supported by the Swiss National Science Foundation (SNF). We thank A. Tsvetkov, who maintains the World Radiation Data Center (WRDC) of the Main Geophysical Observatory in St. Petersburg for providing solar radiation data that have been included in the Global Energy Balance Archive (GEBA). A. Sanchez-Lorenzo was supported by a postdoctoral fellowship from the Regional Government of Catalonia, Spain (2009 BP-
Dimming/brightening research at ETH is supported by the National Centre for Competence in Climate Research (NCCR Climate) of the Swiss National Science Foundation.
Chapter 3

Spatial representativeness of ground-based solar radiation measurements
Spatial representativeness of ground-based solar radiation measurements

Maria Z. Hakuba¹, Doris Folini¹, Arturo Sanchez-Lorenzo¹,², Martin Wild¹

Abstract

The validation of gridded surface solar radiation (SSR) data often relies on the comparison with ground-based in-situ measurements. This poses the question on how representative a point measurement is for a larger-scale surrounding. We use high-resolution (0.03°) SSR data from the Satellite Application Facility on Climate Monitoring (CM SAF) to study the sub-grid spatial variability in all-sky SSR over Europe and the spatial representativeness of 143 surface sites with homogeneous records for their site-centered larger surroundings varying in size from 0.25° to 3°, as well as with respect to a given standard grid of 1° resolution. These analyses are done on a climatological annual and monthly mean basis over the period 2001–2005. The spatial variability of the CM SAF dataset itself agrees very well with surface measurements in Europe, justifying its use for the present study. The annual mean subgrid variability in the 1° standard grid over European land is on average 1.6% (2.4 Wm⁻²), with maximum of up to 10% in Northern Spain. The annual mean representation error of point values at 143 surface sites with respect to their 1° surrounding is on average 2% (3 Wm⁻²). For larger surroundings of 3°, the representation error increases to 3% (4.8 Wm⁻²). The monthly mean representation error at the surface sites with respect to the 1° standard grid is on average 3.7% (4 Wm⁻²). This error is reduced when site-specific correction-factors are applied or when multiple sites are available in the same grid cell, i.e., three more sites reduce the error by 50%.

¹Institute for Atmospheric and Climate Science, ETH Zurich, Switzerland
²Department of Physics, University of Girona, Spain
3.1 Introduction

Ground-based measurements of solar radiation are the most direct way to monitor the evolution of the Earth’s surface energy budget. Networks like the Baseline Surface Radiation Network (BSRN, Ohmura et al. [1998]) provide radiation data of high temporal resolution, quality, and accuracy. These datasets are often used to validate gridded data products originating from climate models or satellite retrieval, which is a vital part of today’s climate research [e.g., Wild et al., 1995, 1998; Pinker et al., 2005; Hatzianastassiou et al., 2005; Bodas-Salcedo et al., 2008; Hinkelman et al., 2009; Freidenreich and Ramaswamy, 2011; Posselt et al., 2012]. The drawback of these data is their geographical coverage, as they originate from point measurements [Wild et al., 2009]. Data from satellite-based measurements and climate models have the advantage of providing full coverage of both the land and the oceans. However, they bear uncertainties due to a variety of constraints and assumptions made in the retrieval processes or parametrization. Specifically, satellite instruments are capable of measuring top-of-atmosphere irradiance with high accuracy, but the retrieval of surface shortwave and longwave fluxes depends heavily on radiative transfer modeling to account for atmospheric attenuation [Wild et al., 1998, 2013].

The validation of both climate model output and satellite products via the comparison of footprint or grid cell means with collocated ground-based SSR measurements is state-of-the-art. Model deviations from observations may not only be caused by uncertainties in retrieval and parametrization, but also by a possible lack of spatial representativeness of the surface sites [e.g., Li et al., 2005]. Li et al. [1995] compared monthly mean SSR from two global satellite-retrieved datasets with in-situ measurements from the Global Energy Balance Archive (GEBA, Ohmura et al. [1989]) and state that large errors are mainly caused by the inadequate spatial representation of point observations within a larger grid cell. Thus, the need to further investigate the point measurements’ representativeness is undeniable [e.g., Wild et al., 1995; Dutton et al., 2006; Hinkelman et al., 2009; Wild et al., 2009; Kato et al., 2012]. For limited areas or networks, e.g., in Southeast Spain [Tovar et al., 1995], Scotland [Glasbey et al., 2001], Belgium [Journé et al., 2012], the FIRE/SRB Wisconsin experiment [Long and Ackermann, 1995], the MESONET in Oklahoma [Barnett et al., 1998], and the ARM network in the Southern Great Plains (Li et al., 2005)), short-term SSR data at high temporal resolution (minutes to days) have been examined with respect to their spatial representativeness based on areal averages, cross-correlations, and cross-covariances. Overall, the results point to decreasing representativeness with increasing distance between points or increasing area size, respectively.

The station sites’ representativeness is also highly dependent on cloud cover and cloud type [e.g., Long and Ackermann, 1995; Barnett et al., 1998], variability in altitude, local topography, and surface type [e.g., Hay, 1984; Tovar et al., 1995]. Temporal averaging and the use of multiple sites to approximate a larger-grid cell’s mean value substantially enhance the spatial representativeness [e.g., Li et al., 1995; Barnett et al., 1998; Li et al., 2005; Journé et al., 2012]. For the study of a point’s spatial representativeness for different spatial scales, the use of high-resolution satellite-retrieved SSR has proven very useful [e.g., Li et al., 2005; Zelenka et al., 1999; Journé et al., 2012].

An alternative approach to compare satellite-retrieved or modeled SSR with point observations is the Meteorological Similarity Comparison Method (MSCM, [Zhang et al., 2010b]), which somewhat bypasses the issue of spatial representativeness by screening the datasets for times when both the ground observation and the collocated model calculation experience similar meteorological conditions. This method requires additional information retrieved from SSR measurements by the Radiative Flux Analysis (RFA) methodology [Long and Ackermann, 1995; Dutton et al., 2006; Hinkelman et al., 2009; Wild et al., 2009; Kato et al., 2012].
3.2 Data and Methods

3.2.1 CM SAF MVIRI

The Satellite Application Facility on Climate Monitoring (CM SAF, www.cmsaf.eu) is part of the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) Satellite Application Facilities (SAFs) network. Within CM SAF, special emphasis is placed on the generation of satellite-derived data records for climate monitoring [Schmetz et al., 2002; Schulz et al., 2009]. The continuous SSR data records are based on the visible channel (0.45–1 µm) of the MVIRI (Visible and Infrared Imager) instruments on-board the Meteosat First Generation (MFG) satellites. The processing employed a climate version of the Heliosat algorithm [Beyer et al., 1996; Cano et al., 1986], which includes a self-calibration method and an improved algorithm for the determination of the clear-sky reflectivity [Posselt et al., 2012]. For more details about the dataset, we refer to Mueller et al. [2011] and Posselt et al. [2011a, 2012]. The mean absolute difference of the monthly mean CM SAF SSR as compared to ground-based observations from the BSRN as a reference is 7.8 Wm$^{-2}$ [Posselt et al., 2011a, b]. The data are available as monthly, daily, and hourly means at 0.03° spatial resolution covering the period 1983–2005. In the present work, we use the monthly mean series covering the period 2001–2005 and refer to it as “cmsaf03”. The spatial domain used here covers most of Europe between -12° to 35° East and 35° to 64° North.

3.2.2 Ground-based observations

The SSR data from the BSRN and GEBA are solely used in the validation of the cmsaf03 dataset (Section 3.3). The only information needed for the further analyses (Section 3.4) is the location of the surface sites, since we use their collocated cmsaf03 pixels as surrogates to assess their spatial representativeness. In the validation, we use SSR as measured by pyranometers,
which are known to have instantaneous accuracy limitations of 3–5% [Michalsky et al., 1999; Wild et al., 2013]. Their accuracy in the field has been estimated by Gilgen et al. [1998], who compared long-term SSR pyranometer measurements of five pairs of stations stored in the GEBA. While the absolute accuracy is unknown, the relative random error of measurement is 5% of the monthly mean and 2% of the yearly mean values. For BSRN-type pyranometer measurements, the GEWEX Radiative Flux Assessment (RFA) [Dutton and Long, 2012] reports operational uncertainties (95% inclusion ranges) of on average ±8 Wm$^{-2}$ for monthly mean and ±6 Wm$^{-2}$ for yearly mean values based on the comparison of redundant measurements at a number of NOAA radiation field sites.

**BSRN** The BSRN is a project of the World Climate Research Program (WCRP), which aims at detecting important changes in the Earth’s radiation fields [Ohmura et al., 1998; Wild et al., 2005] and providing reference data for the assessment of model and satellite-derived SSR. The BSRN provides high-quality surface radiation measurements at around 50 sites worldwide, some of them dating back to the early 1990’s. At these selected sites, covering a latitude range from 80°N to 90°S, SSR is measured with well-calibrated instruments of high accuracy producing 1-min averages from 1-s sampling. The computation of monthly mean values, as used in this study for the validation of the CM SAF data, follows the recommended approach as described in Roesch et al. [2011]. Nine sites from the BSRN as listed in table 3.1 are located in Europe, of which six sites provide sufficient data during the validation period (see Section 3.3). The data is distributed via the World Radiation Monitoring Center (WRMC) hosted by the Alfred Wegener Institute (AWI) in Bremerhaven, Germany (http://www.bsrn.awi.de/).

**GEBA** The GEBA, maintained at the Institute for Atmospheric and Climate Science (IAC) at ETH Zurich, is a database for worldwide measurements of energy fluxes at the Earth’s surface [Gilgen and Ohmura, 1999] and is continuously updated with flux data mainly from the World Radiation Data Centre (WRDC) of the Main Geophysical Observatory in St. Petersburg. It contains more than 2’000 stations with more than 450’000 monthly mean values of various surface energy balance components, mainly downwelling SSR. Many records date back to the 1960s. There are 158 European GEBA stations with monthly data covering at least 3 years within the period 2001–2005, less than 30% data gaps and at least one complete annual cycle. Furthermore, we use only timeseries that prove to be homogeneous during the study period. To address the temporal homogeneity of the GEBA records, we follow the approach as described in Hakuba et al. [2013a], in which four different absolute homogeneity tests are applied to each series. In brief, a timeseries is considered inhomogeneous if at least three out of the four tests indicate a sudden shift in the mean or change in variance. Before applying the homogeneity tests, we removed monthly values that were flagged to be erroneous by the quality control as implemented in the GEBA [Gilgen and Ohmura, 1999]. We find that 140 of the 158 timeseries are considered homogeneous at the 99% significance level. Most of the inhomogeneous station records (18 in total) are located in Switzerland (3), Eastern Europe (6), France (5), and Spain (2). 134 out of 140 temporally homogeneous GEBA records lie within the study domain as defined in Section 3.2.1.

**SwissMetNet** The Swiss Meteorological Network (SwissMetNet) has been established since 2003, renewing and unifying ground-based networks formerly known as ANETZ, ENET, KLIMA, and AERO [Suter et al., 2006]. The data of more than 130 stations include various meteorological parameters at 10-minute temporal resolution. Monthly and annual means
of pyranometer measurements from the Automatic Meteorological Network (ANETZ, 1981–2000) have been compared to BSRN and Alpine Surface Radiation Budget (ASRB) data by Moesch and Zelenka [2004], who suspect the mean values to be afflicted with an uncertainty of 5 to 10%. In the validation process, we use 14 sites located in the Swiss Central Plateau with sufficient data during the study period.

### 3.2.3 1° grid

To exemplify the study of spatial sub-grid variability and representativeness in a gridded dataset, we use the standard 1° equal-angle grid as utilized by the Clouds and Earth’s Radiative Energy System (CERES, Wielicki et al. [1996]) and the NASA/GEWEX Surface Radiation Budget (SRB, e.g., mentioned in Hinkelman et al. [2009], Zhang et al. [2012]). The grid resolution of 1° is also comparable to the spectral resolution T106 as widely used for General Circulation Model (GCM) integrations.

### 3.2.4 Measures of variability and representativeness

To measure the spatial variability of the cmsaf03 SSR data within a given area, i.e., larger-scale grid cell, we use the mean absolute deviation (MAD) as defined in equation 3.1. It quantifies the mean absolute difference between all individual cmsaf03 pixels in the larger area and the corresponding area mean in Wm$^{-2}$. The area size determines the number of cmsaf03 pixels ($n$) to be taken into account for the computation of the statistic. In case of a 1° grid cell, 1089 cmsaf03 pixels are taken into account. MAD is a robust measure of statistical dispersion and, thus, less sensitive to outliers and assumptions about the data distribution than a parametric measure such as the standard deviation ($\sigma$). The relative mean absolute deviation (RMAD, equation 3.2) gives the spatial variability relative to the area mean in %.

$$MAD = \frac{1}{n} \sum_{i=1}^{n} |x_i - \bar{x}|, \quad \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$$

(3.1)

$$RMAD = \frac{MAD}{\bar{x}} \cdot 100$$

(3.2)

We define the spatial sampling error (SSE, equation 3.3) of a point measurement with respect to its larger surrounding as the difference between a surface site’s collocated cmsaf03 pixel value $x_s$ and the surrounding area mean in Wm$^{-2}$. The SSE can be expressed relative to $x_s$, in % (RSSE, equation 3.4). To compute station averages of SSE and RSSE, we consider the absolute (non-negative) errors, referred to as $|SSE|$ and $|RSSE|$.

$$SSE = x_s - \bar{x}, \quad x_s = \text{pixel value}$$

(3.3)

$$RSSE = \frac{SSE}{x_s} \cdot 100$$

(3.4)

The SSE and RSSE are per se site-specific. However, we distinguish between the so-called grid-specific SSE/RSSE, which is calculated with respect to the 1° standard grid (see Section 3.4.3), and the site-centered SSE/RSSE, for which the site is located in the center of a surrounding area of variable size up to 3° (Section 3.4.6). In practice, both, the grid-specific and site-centered SSE/RSSE can be used to calculate correction-factors to improve the site’s representativeness (see Section 3.5.2). The (site-centered) SSE/RSSE represents a characteristic
property of a surface site, quantifying the potential spatial sampling uncertainty associated with its use for the validation of or combination with a gridded dataset.

3.2.5 Clear-sky latitude effect

The prevalent astronomical relations between Sun and Earth induce seasonal and meridional variations in SSR. In the annual mean, the SSR follows a positive North-South gradient on the Northern Hemisphere, which is a crucial factor for the analysis of spatial variability in SSR over larger areas or grid cells. This gradient may induce deviations between point measurements and gridded data simply because they are latitudinally shifted, which we call latitude effect in the following. We approximate this astronomically induced latitude effect at the Earth’s surface by determining the meridional gradient in clear-sky SSR (CM SAF) representative for Europe. To obtain such a gradient, we apply robust regression to the SSR data as a function of latitude for the entire European domain. The resulting annual mean meridional gradient in clear-sky SSR is $3.6 \text{ W m}^{-2} \text{ deg}^{-1}$. With this meridional gradient and an average latitudinal shift of $0.25^\circ$ between a station site collocated with a $1^\circ$ grid cell and its center, the mean latitude effect would be $\pm 0.9 \text{ W m}^{-2}$.

The clear-sky latitude effect varies substantially from season to season and is much smaller in summer (JJA, $1.5 \text{ W m}^{-2} \text{ deg}^{-1}$) than in winter (DJF, $5.1 \text{ W m}^{-2} \text{ deg}^{-1}$).

In the following, we validate the annual mean spatial variability in the cm SAF03 all-sky SSR data. Beforehand, we remove the meridional gradient derived from clear-sky SSR to eliminate the astronomically induced latitude effect. This helps to decrease a spurious correlation between the datasets due to the coinciding North-South gradient in SSR. The study of sub-grid variability and point representativeness is again based on the original all-sky cm SAF03 dataset.

3.3 Validation of spatial variability in CM SAF SSR

A prerequisite for the analysis of spatial representativeness is the adequate representation of spatial variability in the SSR fields given by cm SAF03. Therefore, we validate the spatial variability of cm SAF03 against the spatial variability from GEBA and SwissMetNet station data. For completeness, we also assess the mean biases between BSRN/GEBA and cm SAF03 by comparing the monthly mean all-sky SSR from six European BSRN sites (Camborne, Carpentras, Lerwick, Lindenberg, Payerne, and Toravere) and 134 GEBA sites with sufficient data covering the period 2001–2005, with their collocated cm SAF03 pixels’ timeseries.

We find a mean bias between cm SAF03 and BSRN of $6.55 \text{ W m}^{-2}$ (5.6% of BSRN mean), with RMSE of $10.85 \text{ W m}^{-2}$, which is in good agreement with the validation results by Posselt et al. [2011a, 2012]. The mean bias with respect to the GEBA sites is $6.24 \text{ W m}^{-2}$ (4.46%), with RMSE of $13.72 \text{ W m}^{-2}$ and maximum bias of 21.4% (Rome, Italy), and agrees well with results by Sanchez-Lorenzo et al. [2013]. Both ground-based datasets indicate that cm SAF03 overestimates the monthly mean SSR by around 5%.

However, the absolute accuracy of cm SAF03 is not critical for the purpose of our study. To assess the spatial variability in cm SAF03 over Europe, we compare the MAD (see Section 3.2.4) of the 134 GEBA sites’ climatological annual means (2001–2005) with the MAD of their collocated cm SAF03 pixels. Using a bootstrapping approach, we robustly determine the $\sigma$ and 95% confidence intervals tied to this statistic for both datasets.

The spatial variability of cm SAF03 is with a MAD of $27.05 \text{ W m}^{-2}$ in very good agreement with the GEBA dataset’s MAD of $25.41 \text{ W m}^{-2}$. Removing the mean latitude effect derived
from clear-sky SSR of 3.6 Wm\(^{-2}\)deg\(^{-1}\) (see Section 3.2.5) prior to this analysis, reduces the spatial variability down to 11.77 Wm\(^{-2}\) in cmsaf03, and 11.32 Wm\(^{-2}\) in GEBA. The bias in MAD is then 0.44 Wm\(^{-2}\), indicating a marginal overestimation of about 4% in the spatial variability by cmsaf03.

Using the bootstrapping method, we pick 1’000 random samples from the cmsaf03 and GEBA datasets (clear-sky SSR gradient removed), which results in 1’000 MAD values to calculate confidence intervals with. We find mean (median) MAD values of 11.74 Wm\(^{-2}\) (11.74 Wm\(^{-2}\)) for cmsaf03 and 11.26 Wm\(^{-2}\) (11.28 Wm\(^{-2}\)) for GEBA, with \(\sigma\) of 0.77 Wm\(^{-2}\) and 0.64 Wm\(^{-2}\), and 95% bootstrap confidence intervals of [10.36, 13.19] for cmsaf03 and [10.24, 12.66] for GEBA (bias corrected and accelerated percentile method [Efron, 1987]). The two-dimensional density plot (Figure 3.1) illustrates the distribution of the random samples’ MAD for both datasets with their median (green dot) and the 1:1 line, and supports the finding of an excellent agreement with only a slightly larger MAD in the cmsaf03 dataset.

To assess the spatial variability in cmsaf03 with a denser network, we perform the same analysis with 14 stations of the SwissMetNet located in the Swiss central plateau. The MAD of cmsaf03 and SwissMetNet are 2.52 Wm\(^{-2}\) and 2.72 Wm\(^{-2}\), which means cmsaf03 underestimates the spatial variability in the Swiss Central Plateau by 0.2 Wm\(^{-2}\) or about 7%. The mean MAD of the 1’000 random samples is 2.55 Wm\(^{-2}\) for cmsaf03 and 2.66 Wm\(^{-2}\) for the SwissMetNet data, with \(\sigma\) of 0.89 Wm\(^{-2}\) and 0.58 Wm\(^{-2}\), and 95% bootstrap confidence intervals of [1.27, 4.57] and [1.82, 4.19].

Both analyses point to good agreement (on average 7% or better) in spatial variability between cmsaf03 and the ground observations. Thus, we conclude that cmsaf03 reasonably captures the general spatial variability across the European study domain and can be used to quantify the spatial representativeness of the European surface sites by using their collocated cmsaf03 pixels as surrogates.


3.4 Results

3.4.1 Spatial small-scale variability in SSR

We analyze the annual mean SSR as given by the high-resolution cmsaf03 data to identify regions in Europe of large spatial small-scale variability. Figure 3.2 (left) depicts the annual mean SSR (2001–2005) over Europe, whereas Figure 3.2 (right) depicts the variability within every 0.03° pixels’ 1° surrounding (pixel is center of a square) in terms of RMAD (see Section 3.2.4). Regions where steep gradients in SSR exist are likewise regions of large spatial (1°) variability with maximum RMAD of 10.5% found in Northern Spain.

Figure 3.3 depicts the |RSSE| of each cmsaf03 pixel in the domain with respect to its 1° surrounding. Pixels that have large |RSSE| (reddish colors) are less representative for their larger surrounding than pixels with small |RSSE| (yellowish colors). As expected, pixels with large |RSSE| are located in regions of large spatial variability (RMAD, Figure 3.2), the maximum of 18% lies in Northern Spain.

3.4.2 SSR sub-grid variability on a 1° grid

Large RMAD indicates that at least some pixels in the corresponding region will also have large |RSSE|. Here, we determine for a 1° standard grid (Section 3.2.3), where grid cells with large RMAD are located and whether RMAD has any dependence on season.

We calculate the RMAD within every 1° grid cell in the standard grid on a climatological basis, for annual mean SSR (2001–2005), winter (DJF), and summer (JJA). Figure 3.4 (left) depicts the annual mean cmsaf03 SSR aggregated onto the 1° grid. Although the main features of the spatial pattern are captured, the small-scale variability is lost when decreasing the spatial resolution. Naturally, the high-resolution cmsaf03 data capture the local SSR gradients, such as in Northern Spain, more realistically. Figure 3.4 (right) depicts the sub-grid variability (RMAD). As expected, it is largely in line with the spatial variability pattern as shown in Figure 3.2 (right). Most of the critical grid cells are thus located in Northern Spain, the Alpine region, the Carpathians and the Adriatic coast. The maximum of around 10% is again found in Northern Spain.

On average, RMAD (MAD) is 1.6% (2.4 Wm$^{-2}$) over European land (including oceans: 1.3% or 2 Wm$^{-2}$), based on our analysis for annual mean radiation in Europe. There are 842
Figure 3.3: Annual mean (2001–2005) |RSSE| (%) of every cmsaf03 pixel with respect to its 1° surrounding (square).

1° grid cells over land (1’392 in entire domain) of which 10% exceed a sub-grid variability of 5.04 Wm$^{-2}$ (3.13%). In winter (not shown), the RMAD is the largest in Norway. However, the amount of solar radiation is very small (between 20 and 40 Wm$^{-2}$). Stating large variability in SSR is thus redundant. Compared to the annual mean, the Alps and Pyrenees remain as critical regions with even larger RMAD. In summer (not shown), the pattern in sub-grid variability is similar to the annual mean, also in magnitude. Although the SSR variability depends on weather conditions, the seasons of high insololation dominate the annual pattern. Hence, we focus on the annual mean pattern to assess the BSRN and GEBA sites’ representativeness for their collocated 1° grid cells.

As expected, subtracting the annual mean clear-sky latitude effect reduces the average MAD and RMAD down to 1.76 Wm$^{-2}$ and 1.21% (European land). However, this reduction appears very small. In some grid cells, local (cloud) effects have masked or even reversed the meridional gradient in SSR, which means that subtracting the clear-sky gradient induces enhanced dispersion and, thus, sub-grid variability. Further analysis is again based on the original all-sky cmsaf03 SSR data.

3.4.3 Representativeness of points for 1° grid cells

The sub-grid variability (MAD, RMAD) alone is not a sufficient measure for the representativeness of an individual observation site for its collocated larger-grid cell. Despite large MAD, the value at the location of the site can be close to the grid cell mean. Thus, it is particularly necessary that the site’s |SSE| is small. To obtain a “worst case” estimate for representativeness, we additionally calculate the maximum possible SSE (MAX) and RSSE (RMAX) associated with an arbitrary cmsaf03 pixel located within the surface sites’ collocated 1° grid cell. The MAX and RMAX account for a slight shift in site or grid cell location, which could substantially change the site-specific RSSE.

In the following, we assess the representativeness of 143 surface sites (9 BSRN, 134 GEBA) by comparing their cmsaf03 surrogate with the 1° grid cell mean to obtain the SSE (RSSE).
The concrete case of BSRN sites

The geographical location of the 9 BSRN sites (crosses) and their collocated grid cells with RSSE in color (squares) are shown in Figure 3.5 (left). The station average |SSE| and |RSSE| are 4.79 Wm$^{-2}$ and 3.04% ($\sigma$: 3.28 %) with largest |RSSE| of +8.66% (SSE: 16.5 Wm$^{-2}$) in Carpentras (France) and -7.7% (SSE: -13 Wm$^{-2}$) in Cener (Spain). Both sites are located in areas of large spatial variability with RMAD exceeding 5%. The station average |RMAX| (MAX) is 7.27% (11.26 Wm$^{-2}$), more than double the sites’ average |RSSE|. Table 3.1 presents for every BSRN site in Europe and its collocated 1° grid cell the SSE (RSSE), MAD (RMAD), and MAX (RMAX).

Table 3.1: BSRN sites’ SSE (Wm$^{-2}$), RSSE (% in brackets), MAD (Wm$^{-2}$), RMAD (% in brackets), MAX (Wm$^{-2}$) and RMAX (% in brackets) with respect to their collocated 1° grid cells.
The concrete case of GEBA sites

Four of the 134 GEBA sites lie on the border of two grid cells and are assigned to both, in these cases two grid cells are included in the analysis. In 13 cases, multiple GEBA sites (max. 4) are collocated with a $1^\circ$ grid cell, but are treated as individual site-grid cell pairs. Hence, in total, we evaluate 138 site-grid cell pairs, although only 118 individual $1^\circ$ grid cells are collocated with the 134 GEBA sites.

In table 3.2, we summarize the statistics of the SSE (RSSE), MAD (RMAD), and MAX (RMAX). The station average SSE and RSSE are 0.78 Wm$^{-2}$ and 0.4%, respectively. The station average $|SSE|$ and $|RSSE|$ are 3.2 Wm$^{-2}$ and 2.1%. The largest RSSE of 10.8% is found at the site in Lugano, Switzerland. The station average $|RMAX|$ is with 7% more than 3 times larger than the GEBA sites’ average $|RSSE|$, i.e., the grid cells could be less well represented by other arbitrary cmSaf03 pixels located within them.

90% of the GEBA sites considered here, are located within grid cells of less than 3.5% RMAD and with $|RSSE|$ smaller than 4.7%. 70% of the sites are located within grid cells of less than 2.2% RMAD and have $|RSSE|$ smaller than 2.4%.

Table 3.2: Statistics of GEBA sites’ SSE (Wm$^{-2}$), RSSE (%), MAD (Wm$^{-2}$), RMAD (%), MAX (Wm$^{-2}$) and RMAX (%) with respect to their collocated $1^\circ$ grid cells in the standard grid. Statistics are based on 138 site-grid cell pairs. Footnotes indicate surface sites with maximum/minimum $|RSSE|$, RMAD, and $|RMAX|$.

<table>
<thead>
<tr>
<th>GEBAnStats</th>
<th>SSE (RSSE)</th>
<th>MAD (RMAD)</th>
<th>MAX (RMAX)</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>0.78 (0.4)</td>
<td>2.9 (1.93)</td>
<td>-6.48 (-3.67)</td>
</tr>
<tr>
<td>mean (abs.)</td>
<td>3.2 (2.1)</td>
<td>2.9 (1.93)</td>
<td>10.64 (7.01)</td>
</tr>
<tr>
<td>median</td>
<td>0.77 (0.54)</td>
<td>2.28 (1.75)</td>
<td>-7.2 (-4.44)</td>
</tr>
<tr>
<td>median (abs.)</td>
<td>2.34 (1.72)</td>
<td>2.28 (1.75)</td>
<td>9.08 (6.42)</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>4.43 (2.85)</td>
<td>1.92 (1.16)</td>
<td>10.73 (7.07)</td>
</tr>
<tr>
<td>max (abs.)</td>
<td>17.46 (10.84)$^a$</td>
<td>10.5 (5.77)$^b$</td>
<td>36.75 (20.21)$^b$</td>
</tr>
<tr>
<td>min (abs.)</td>
<td>&lt;0.01 (&lt;0.01)$^c$</td>
<td>0.5 (0.38)$^d$</td>
<td>2.05 (1.59)$^e$</td>
</tr>
</tbody>
</table>

$^a$Lugano, Switzerland; $^b$Vitoria, Spain; $^c$Norrköping, Sweden; $^d$Oostende, Netherlands; $^e$Constanta, Romania
Figure 3.6: Mean annual cycles (2001–2005) of monthly $|\text{SSE}|$ in Wm$^{-2}$ (left) and $|\text{RSSE}|$ in % (right) of 138 site-grid cell pairs (GEBA dataset wrt. standard grid). The blue thick line is the station average annual cycle, the green shading indicates the 95% bootstrap confidence intervals.

To depict the RSSE with respect to the 118 grid cells as collocated with the 134 GEBA sites (Figure 3.5, right), we average the annual mean SSR over multiple GEBA sites if more than one site is collocated with a larger-grid cell, and calculate the RSSE thereafter. This leads to slightly lower average RSSE and $|\text{RSSE}|$ of 0.46% and 1.76%. The reduction in RSSE through the use of multiple sites to approximate the larger-grid cell mean is discussed in Section 3.4.7. The 12 grid cells with $|\text{RSSE}|$ exceeding 3.7% (90th percentile) lie in Great Britain (4), on the Iberian Peninsula (4), and in the Alpine region and Northern Italy (4).

3.4.4 Monthly mean $|\text{SSE}|$ and $|\text{RSSE}|$

The monthly mean $|\text{SSE}|$ and $|\text{RSSE}|$ over the period 2001–2005 reveal a distinct annual cycle. On average, the monthly mean $|\text{SSE}|$ and $|\text{RSSE}|$ at the 134 GEBA sites with respect to the 1° standard grid are 5 Wm$^{-2}$ (median: 4.1 Wm$^{-2}$, $\sigma$: 3 Wm$^{-2}$) and 4.3% (median: 3.5%, $\sigma$: 2.7%). Figure 3.6 depicts the corresponding 5-year mean annual cycles of $|\text{SSE}|$ (left) and $|\text{RSSE}|$ (right). The blue curve represents the mean annual cycle averaged over all stations, the green shadings illustrate the 95% bootstrap confidence intervals. The seasonal cycles of $|\text{SSE}|$ and $|\text{RSSE}|$ averaged over all stations are opposing: $|\text{SSE}|$ is larger in the summer months, reaching up to 7 Wm$^{-2}$ ($|\text{RSSE}|$: 3%) in July, $|\text{RSSE}|$ peaks in December with 7.5% ($|\text{SSE}|$: 2.6 Wm$^{-2}$). Overall, the monthly mean $|\text{SSE}|$ and $|\text{RSSE}|$ are of the same magnitude as the climatological annual mean $|\text{SSE}|$ (3.2 Wm$^{-2}$) and $|\text{RSSE}|$ (2.1%).

3.4.5 Temporal evolution of RSSE

We examine the temporal variability, including potential trends, of the grid-specific RSSE at nine BSRN and 134 GEBA sites. For this purpose, we use cmsaf03 timeseries of 11-years length (1995–2005). The temporal variability in annual mean RSSE at the nine BSRN sites with respect to the 1° grid is shown in Figure 3.7. The series show no systematic trends at the 90% significance level (t-test), but a year-to-year variability of around ±1% is evident. The climatological averages of $|\text{RSSE}|$ over five (2001–2005, RSSE: 3.04%) and eleven years (1995–2005, RSSE: 2.97%) are robust and do not significantly differ. The same analysis performed with the cmsaf03 surrogates at the 134 GEBA sites shows that 20 timeseries of annual mean RSSE have significant trends, of which 12 are positive and 8 are negative with a mean
3.4 RESULTS

Figure 3.7: Timeseries of annual mean RSSE (1995–2005) with respect to the 1° standard grid based on cmsaf03 SSR at nine BSRN sites in Europe (%).

absolute trend of $0.1\%_{yr^{-1}}$. Also for the GEBA dataset, the 5-year mean RSSE agrees very well with the 11-year mean.

3.4.6 Point representativeness versus grid cell size

The spatial representativeness of a surface site can be quantified independent of a predefined grid. Based on the cmsaf03 data, we calculate the surface sites’ $|\text{RSSE}|$ with respect to surrounding grid cells of variable size. In Figure 3.8 (BSRN left, GEBA right) the $|\text{RSSE}|$ of each site is shown as a function of surrounding area from 0.03° to 3°. In tables 3.3 and 3.4, we summarize the BSRN and GEBA sites’ SSE, $|\text{SSE}|$, RSSE, and $|\text{RSSE}|$ with respect to 0.25°, 0.5°, 1°, 2°, and 3° surroundings. This “grid” range covers many of the modeling and satellite-derived datasets available over Europe. The analysis highlights several things: 1) Even for area sizes of up to 3° the mean $|\text{SSE}|$ does not exceed 5 Wm$^{-2}$; considering the GEBA dataset, we find a mean $|\text{SSE}|$ of 4.8 Wm$^{-2}$ and $|\text{RSSE}|$ of 3.1% for 3° grid cells. 2) For some individual stations, and also in the mean and median curves (red and green), a steep increase in $|\text{RSSE}|$ at smaller distances and a leveling-off thereafter is evident. This makes especially sense for surface sites that lie in regions of large small-scale variability, e.g., in or near mountain ranges like the BSRN site Payerne or near coast lines like the BSRN site Lerwick. At stations located in regions with no strong SSR variability, the curve stays rather flat (e.g., Lindenberg). At Carpentras, on the other hand, the absolute $|\text{RSSE}|$ seems to grow quadratically with increasing grid cell size. The GEBA station average curve (Figure 3.8, right, red line) is well-represented ($R^2=0.98$) by the logarithmic function: $0.74 \cdot \ln(x) + 2.2$, where $x$ is the surrounding grid cell size in degrees. This function allows for a first order estimate of the $|\text{RSSE}|$ as function of the grid cell size.

Similar to the grid-specific RSSE (Section 3.4.5), the site-centered $|\text{RSSE}|$ varies from year to year. The year-to-year (2001–2005) variability of the $|\text{RSSE}|$ averaged over all grid cell sizes is $\pm 0.4\%$ for the GEBA dataset and has the tendency to increase with increasing grid cell size, reaching at most $\pm 0.7\%$ with respect to the 3° surrounding.
### Table 3.3: BSRN sites’ site-centered SSE (Wm\(^{-2}\)) and RSSE (%) with respect to their larger surroundings (squares) of 0.25°, 0.5°, 1°, 2°, and 3° resolution.

<table>
<thead>
<tr>
<th>BSRN site</th>
<th>0.25°</th>
<th>0.5°</th>
<th>1°</th>
<th>2°</th>
<th>3°</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cabauw</td>
<td>0.69 (0.55)</td>
<td>0.99 (0.78)</td>
<td>0.76 (0.6)</td>
<td>0.82 (0.65)</td>
<td>0.32 (0.25)</td>
</tr>
<tr>
<td>Camborne</td>
<td>-2.05 (-1.55)</td>
<td>-2.39 (-1.81)</td>
<td>-2.57 (-1.94)</td>
<td>-1.87 (-1.41)</td>
<td>-1.03 (-0.77)</td>
</tr>
<tr>
<td>Carpentras</td>
<td>1.58 (0.83)</td>
<td>4.7 (2.47)</td>
<td>10.68 (5.62)</td>
<td>16.99 (8.95)</td>
<td>19.40 (10.22)</td>
</tr>
<tr>
<td>Cener</td>
<td>3.8 (2.25)</td>
<td>2.13 (1.26)</td>
<td>-2.30 (-1.36)</td>
<td>-4.75 (-2.81)</td>
<td>-5.80 (-3.44)</td>
</tr>
<tr>
<td>Lerwick</td>
<td>3.4 (3.27)</td>
<td>3.96 (3.81)</td>
<td>4.09 (3.94)</td>
<td>3.61 (3.48)</td>
<td>3.02 (2.91)</td>
</tr>
<tr>
<td>Lindenberg</td>
<td>-0.62 (-0.51)</td>
<td>-0.67 (-0.55)</td>
<td>-0.19 (-0.16)</td>
<td>-0.43 (-0.35)</td>
<td>-2.14 (-1.76)</td>
</tr>
<tr>
<td>Palaiseau</td>
<td>-0.25 (-0.18)</td>
<td>-0.7 (-0.5)</td>
<td>-0.77 (-0.56)</td>
<td>-0.81 (-0.59)</td>
<td>-0.79 (-0.57)</td>
</tr>
<tr>
<td>Payerne</td>
<td>3.46 (2.29)</td>
<td>5.8 (3.84)</td>
<td>5.76 (3.81)</td>
<td>4.09 (2.71)</td>
<td>2.02 (1.34)</td>
</tr>
<tr>
<td>Toravere</td>
<td>0.23 (0.2)</td>
<td>0.29 (0.25)</td>
<td>0.43 (0.37)</td>
<td>&lt;0.01 (&lt;0.01)</td>
<td>0.20 (0.17)</td>
</tr>
<tr>
<td><strong>mean</strong></td>
<td>1.14 (0.79)</td>
<td>1.57 (1.06)</td>
<td>1.77 (1.15)</td>
<td>1.96 (1.18)</td>
<td>1.67 (0.93)</td>
</tr>
<tr>
<td><strong>mean (abs.)</strong></td>
<td>1.78 (1.29)</td>
<td>2.4 (1.7)</td>
<td>3.06 (2.04)</td>
<td>3.71 (2.33)</td>
<td>3.86 (2.38)</td>
</tr>
<tr>
<td><strong>median</strong></td>
<td>0.69 (0.54)</td>
<td>0.99 (0.78)</td>
<td>0.43 (0.37)</td>
<td>&lt;0.01 (&lt;0.01)</td>
<td>0.2 (0.17)</td>
</tr>
<tr>
<td><strong>median (abs.)</strong></td>
<td>1.58 (0.83)</td>
<td>2.13 (1.26)</td>
<td>2.30 (1.36)</td>
<td>1.87 (1.42)</td>
<td>2.02 (1.34)</td>
</tr>
<tr>
<td><strong>std</strong></td>
<td>2.06 (1.54)</td>
<td>2.77 (1.98)</td>
<td>4.32 (2.65)</td>
<td>6.24 (3.49)</td>
<td>7.11 (3.92)</td>
</tr>
</tbody>
</table>

### 3.4.7 Multiple sites’ representativeness

To assess whether the averaging over multiple surface sites improves the approximation of a grid cell mean, we randomly select 1’000 times up to 50 cmsaf03 surrogates within every 1° cell (standard grid) over Europe land (842 grid cells) and calculate the |RSSE| as a function of “station site” number. The 842 resulting curves are shown in Figure 3.9 (gray lines) and are overlaid by some statistically relevant examples as described in the following. The black thick line is the average of all considered grid cells. Critical high-variability grid cells (exceeding the 95\(^{th}\) percentile of RMAD=4.03%) yield the blue dashed lines with their average in thick blue. The green dashed lines depict the functions of the least critical (below the 5\(^{th}\) percentile, RMAD=0.55%) grid cells with their average as thick green line. The most critical grid cell is located in Northern Spain (red dashed). On average (black curve), three sites within a grid cell are sufficient to reduce the |RSSE| from 1.6% (when only one site is found within a grid cell) down to 1%. The situation is different for the critical grid cells, as far more points, on average 24, are needed to reach an |RSSE| of only 1%. For the most critical grid cell not even 50 points are enough to reduce the |RSSE| down to 1%.

On average and for the critical and less critical grid cells, adding 3 more sites would be sufficient to half the |RSSE|, but the strongest improvement occurs when adding a second site. The improvement is most efficient in critical grid cells indicated by the steeper slopes as compared to the mean average curve.

### 3.4.8 Synthesis: Uncertainties

The spatial sampling uncertainty depends on the grid resolution, the specific location of the surface site within the collocated grid cell, and the spatial sub-grid variability.

The spatial subgrid-variability (MAD, RMAD) constitutes a rather loose uncertainty estimate that may serve as an indicator for the site-specific SSE and RSSE and is on average 2% for both the BSRN and GEBA datasets in the 1° standard grid.

The climatological annual mean |RSSE| (|SSE|) is on average 3% (5 Wm\(^{-2}\)) at nine BSRN, and around 2% (3 Wm\(^{-2}\)) at 134 GEBA sites, and represents a more realistic and site-specific
Table 3.4: Statistics of GEBA sites’ site-centered SSE (Wm\(^{-2}\)) and RSSE (%), in brackets) with respect to their larger surroundings (squares) of 0.25°, 0.5°, 1°, 2°, and 3°. Statistics are based on 134 GEBA sites. Footnotes indicate observation sites with maximum and minimum RSSE, respectively.

<table>
<thead>
<tr>
<th>GEBA SSE &amp; RSSE</th>
<th>0.25°</th>
<th>0.5°</th>
<th>1°</th>
<th>2°</th>
<th>3°</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>0.6 (0.33)</td>
<td>0.9 (0.48)</td>
<td>0.72 (0.3)</td>
<td>0.41 (-0.02)</td>
<td>0.05 (-0.34)</td>
</tr>
<tr>
<td>mean (abs.)</td>
<td>1.81 (1.18)</td>
<td>2.53 (1.65)</td>
<td>3.2 (2.08)</td>
<td>4.22 (2.75)</td>
<td>4.82 (3.14)</td>
</tr>
<tr>
<td>median</td>
<td>0.58 (0.35)</td>
<td>0.7 (0.47)</td>
<td>0.58 (0.44)</td>
<td>0.33 (0.3)</td>
<td>-0.19 (-0.14)</td>
</tr>
<tr>
<td>median (abs.)</td>
<td>1.17 (0.81)</td>
<td>2.04 (1.27)</td>
<td>2.43 (1.6)</td>
<td>3.35 (2.24)</td>
<td>3.88 (2.57)</td>
</tr>
<tr>
<td>std</td>
<td>2.56 (1.68)</td>
<td>3.3 (2.16)</td>
<td>4.22 (2.74)</td>
<td>5.7 (3.64)</td>
<td>6.48 (4.12)</td>
</tr>
<tr>
<td>max (abs.)</td>
<td>12.18 (7.47)(^a)</td>
<td>13.45 (8.25)(^e)</td>
<td>13.92 (8.53)(^e)</td>
<td>19.84 (13.35)(^b)</td>
<td>22.84 (15.36)(^b)</td>
</tr>
<tr>
<td>min (abs.)</td>
<td>0.02 (0.01)(^c)</td>
<td>0.01 (0.01)(^d)</td>
<td>0.02 (0.01)(^e)</td>
<td>0.01 (0.01)(^d)</td>
<td>0.02 (0.02)(^g)</td>
</tr>
</tbody>
</table>

\(^a\)Sion, Switzerland; \(^b\)San Sebastian, Spain; \(^c\)Umea, Sweden; \(^d\)Dijon, France; \(^e\)Zoseni, Latvia; \(^f\)Vigna Valle, Italy; \(^g\)Oestersund, Sweden

uncertainty estimate. 90% of the cmsaf03 surrogates collocated with the 134 GEBA sites have \(|\text{RSSE}|\) smaller than 4.7%. The monthly mean \(|\text{SSE}|\) and \(|\text{RSSE}|\) (2001–2005) are 5 Wm\(^{-2}\) and 4% and of similar magnitude as the climatological annual mean values.

The site-specific RSSE values are robust over different time periods, but the year-to-year variability might add another 1% on top of the climatological uncertainty estimates.

3.5 Discussion

Besides relating our study to previous works (Section 3.5.1), we furthermore suggest a “poor man’s” approach to improve the surface sites’ representativeness with respect to the 1° standard grid (Section 3.5.2). This “correction” approach takes into account the clear-sky latitude effect (see Section 3.2.5) and the site-centered SSE/RSSE with respect to a 1° surrounding grid cell (Section 3.4.6).

3.5.1 Comparison with previous studies

The central question of the present study is: How well does a point measurement represent the area mean of its larger surrounding? Most similar to our approach, yet differing in spatial and temporal extent, is the study by Li et al. [2005]. Using SSR data retrieved from the Geostationary Operational Environmental Satellite (GOES) and ground-based SSR measurements from the Atmospheric Radiation Measurement (ARM) Southern Great Plains (SGP) site, Li et al. [2005] studied the difference between the point observations’ surrogate data (GOES) and area-means for different months (in 2000), grid sizes (up to 400 x 400 km\(^2\)), and integration intervals. From their Figure 5, we deduce a monthly mean sampling error between 4 and 5 Wm\(^{-2}\) for a 100 x 100 km\(^2\) grid cell, largely in line with our monthly mean \(|\text{SSE}|\) of 5 Wm\(^{-2}\) with respect to the 1° standard grid.

Furthermore, Li et al. [2005] show how the use of multiple sites (up to 21) to approximate the area mean decreases the SSE. This effect is strongest using 2 or 3 sites instead of 1 site within a 200 x 200 km\(^2\) domain. In addition to that, our study based on the cmsaf03 surrogates shows that the reduction of \(|\text{RSSE}|\) is most efficient for grid cells of high spatial sub-grid variability. In general, our study can be seen as an expansion of the approach of Li et al. [2005] to a broader and more heterogeneous spatial domain, including a larger number of existing surface sites’ locations, and estimating monthly and annual mean SSE/RSSE over a longer time period.
Another class of studies uses correlations between SSR timeseries from different observation sites to quantify spatial representativeness. In general, our results are in good agreement with such studies as well, even though a direct comparison is not feasible. Tovar et al. [1995] found a correlation between SSR variability and elevation differences between station pairs, which means orography interferes with the distance related error. In line with that, we find the highest sub-grid variability and largest SSE/RSSE in mountainous regions like the Alps or Pyrenees, clearly also influenced by meso-scale meteorology.

Various studies showed that averaging over longer time intervals improves the correlation between station pairs, i.e., their representativeness for larger surroundings [e.g., Barnett et al., 1998; Li et al., 2005; Journée et al., 2012]. Here, we use monthly and annual mean SSR data, which a priori lead to lower SSE and RSSE than using daily or sub-daily means. The monthly and annual means reflect mean weather conditions and climate regimes instead of diurnal variations, and are widely used in energy budget studies [e.g., Stephens et al., 2012; Wild et al., 2013] or the validation of (non-deterministic) climate models [e.g., Wild et al., 1995; Wild, 2005; Wild and Schmucki, 2011].

### 3.5.2 Correcting for SSE

The consequences of omitting sites because of their low representativeness is to be debated. Losing sites in low-variability regions that are otherwise well-covered by other, more representative sites, is certainly less problematic than losing a site in a sparsely covered area. Also, omitting sites in high-variability regions per se might be critical, as valuable information will be lost in these regions. On the other hand, it is questionable whether sites in high-variability regions can ever be truly representative for their larger surrounding even though the SSE appears small by coincidence. We suggest that decisions on accuracy requirements and data omission depend on the respective datasets and their application, and should be evaluated case-specifically. A viable alternative to adequately compare modeled data with point observations in high-variability regions is the MSCM method [Zhang et al., 2010b], as briefly introduced in Section 3.1. However, in contrast to the BSRN, the GEBA does not fulfill the data requirements of this method, as it provides only monthly mean radiation flux data.
Resting upon the results presented here it is possible to improve a surface site’s representativeness with respect to the 1° standard grid, i.e., to obtain an SSE-free representation of the collocated grid cell mean by an appropriate correction. This can be achieved by computing correction-factors based on the monthly or annual mean SSE or RSSE. For this purpose, the present study would have to be repeated for any grid specification other than the 1° grid discussed here, which is time consuming and requires access to high-resolution datasets such as the cmsaf03. To circumvent this procedure, we exemplify a pragmatic “poor man’s“ approach using the site-specific latitude effect and site-centered RSSE, instead of using the “true“ grid-specific RSSE. This approach appears useful, as for both the BSRN and GEBA dataset, the grid-specific RSSE and site-centered RSSE are strongly correlated (R^2: 0.9).

In Figure 3.10, we show at nine BSRN sites the change in RSSE (black circles) due to a correction based on the clear-sky latitude effect (green), the correction based on the site-centered RSSE (blue) for a 1° surrounding, and the combination of latitude effect and site-centered RSSE (red). The horizontal zero line (black dashed) indicates perfect correction to be obtained by using the grid-specific correction-factor.

For seven sites, the RSSE improves by both the site-centered and combined adjustment (filled blue and red circles), and the circles move closer to the zero line. The latitude effect alone improves only four sites’ RSSE. For two sites (Cabauw and Lindenberg) that seem highly representative and lie within low-variability grid cells, the correction approach increases the RSSE slightly, which is mostly due to the latitude-effect correction. For three sites with large RSSE (Carpentras, Payerne, and Lerwick), the improvement is more efficient and mostly due to the site-centered adjustment.

On average, the |RSSE| of 3% is reduced down to 1.3% due to the combined correction, which constitutes an improvement of almost 60%. Considering only the seven sites, for which the |RSSE| indeed decreases due to combined correction, leads to an improvement of even 75%. Also for GEBA, a reduction in RSSE can be achieved by combining the latitude effect and site-centered correction factors. The mean |RSSE| of 2.1% is halved down to 1.07%.
40  

CHAPTER 3: SPATIAL REPRESENTATIVENESS – EUROPE

Figure 3.10: Change in RSSE with respect to the 1° standard grid (black circles) at nine BSRN sites due to a “poor man’s” correction approach, which is based on the latitude effect (green), the site-centered adjustment for a 1° surrounding (blue), or their combination (red). Filled circles indicate improvement of representativeness due to the correction approach.

With the help of this data and table 3.3 (BSRN), an interested reader should be able to optimize the representativeness of the GEBA and BSRN sites with respect to a specific grid between 0.25° and 3° he/she may use in an application. These tables may also provide guidance on the selection of appropriate surface radiation sites in Europe depending on the accuracy requirements of a particular application.

3.6 Summary and Conclusions

In the present work, we addressed the question of how representative a point measurement of surface solar radiation (SSR) is for its larger surrounding, such as a grid cell of a climate model or satellite data product. We define the representativeness of a measurement site by means of the relative spatial sampling error (RSSE) and the relative mean absolute deviation (RMAD). RSSE compares the site value to the area mean value. RMAD compares the variability within the area to the area mean, thus can be seen as a measure of SSR sub-grid-scale variability. To quantify RSSE and RMAD, we used the high-resolution (0.03°) SSR data from the Satellite Application Facility on Climate Monitoring (CM SAF). Regions of large spatial sub-grid variability are mostly located in mountainous regions, such as the Pyrenees, Alps, and Carpathians. The mean MAD and RMAD in the 1° standard grid are 2.4 Wm\(^{-2}\) and 1.6% over Europe land.

The site-specific |RSSE| at nine BSRN and 134 GEBA sites with respect to their collocated 1° grid cell varies from almost 0% to more than 10%. The |RSSE| over all BSRN and GEBA sites is 3% (5 Wm\(^{-2}\)) and 2% (3 Wm\(^{-2}\)), respectively, on a climatological annual mean (2001–2005) basis. 90% of the GEBA sites considered here are associated with |RSSE| smaller than 4.7%. Considering the GEBA dataset, the monthly mean |RSSE| during 2001–2005 is on average 4% and clearly of the same order as the climatological uncertainty estimates.

The site-centered |RSSE| represents a characteristic property of the surface sites and is on average 2% (3 Wm\(^{-2}\)) with respect to a 1° surrounding grid cell and around 3% (5 Wm\(^{-2}\)) for a 3° surrounding grid cell. Furthermore, it is a suitable indicator for the grid-specific RSSE.
and can be used to approximate correction-factors to enhance the representativeness of a site for a larger surrounding. With 2–3% (3–5 W m\(^{-2}\)), the error magnitude is on the order of the accuracy limitations associated with pyranometer measurements (5% of monthly, 2% of yearly means [Gilgen et al., 1998]).

Using multiple sites to better approximate the area mean of a larger surrounding (1° grid cell) works most efficiently for grid cells that exhibit high spatial sub-grid variability. Adding one more (potential) site reduces the RSSE most efficiently, adding three more sites halves the RSSE.

In a forthcoming study, one could spatially expand the present work by analyzing the cm-saf03 data over the entire Meteosat Disk and assess the spatial variability over large portions of Africa and South America and thus in other climate regimes. This study is part of a project that aims at the computation of atmospheric solar absorption based on the combination of ground-based SSR measurements with collocated satellite-retrieved top-of-atmosphere irradiance. Knowledge about the surface sites’ spatial representativeness is essential to narrow down the uncertainty range associated with this analysis.

Acknowledgments

This study is funded by the Swiss National Science Foundation Grant No. 200021 135395 (“Towards an improved understanding of the Global Energy Balance: absorption of solar radiation”). A. Sanchez-Lorenzo was supported by a postdoctoral fellowship from the government of Catalonia (2011 BP-B) and the project NUCLIEROSOL (CGL2010-18546). We would like to thank Christoph Schär for his continuous support of our work and Guido Müller and Stefanos Mystakidis for the maintenance of the GEBA. Furthermore, we thank Reto Stöckli and Jörg Trentmann for providing the CM SAF MVIRI dataset and their expertise.
Chapter 4

Spatial representativeness of ground-based solar radiation measurements – Extension to the full Meteosat disk
Spatial representativeness of ground-based solar radiation measurements – Extension to the full Meteosat disk

Maria Z. Hakuba\(^1\), Doris Folini\(^1\), Arturo Sanchez-Lorenzo\(^2\,\(^3\), Martin Wild\(^1\)

Abstract

The spatial representativeness of a point measurement of surface solar radiation (SSR) of its larger-scale surrounding, e.g. collocated grid cell, is a potential source of uncertainty in the validation of climate models and satellite products. Here, we expand our previous study over Europe to the entire Meteosat disk, covering additional climate zones in Africa, the Middle east, and South America between -70\(^\circ\) to 70\(^\circ\) East and -70\(^\circ\) to 70\(^\circ\) North. Using a high-resolution (0.03\(^\circ\)) satellite-based SSR dataset (2001–2005), we quantify the spatial subgrid variability in grids of 1\(^\circ\) and 3\(^\circ\) resolution and the spatial representativeness of 887 surface sites with respect to site-centered surroundings of variable size. In the multi-annual mean the subgrid variability is the largest in some mountainous and coastal regions, but varies seasonally due to changes in the ITCZ location. The absolute mean representation errors at the surface sites with respect to surroundings of 1\(^\circ\) and 3\(^\circ\) are on average 1-2% (3 Wm\(^{-2}\)) and 2-3% (4 Wm\(^{-2}\)), respectively. The majority of sites are found to be representative within the in-situ measurement accuracy. We show that their site-specific representativeness can be reliably approximated by the subgrid variability in a fixed grid (1\(^\circ\)). The subgrid variability in turn is only moderately reduced when computed from coarser grid data, typically the only data available in areas not covered by the 0.03\(^\circ\) resolved Meteosat disk. Together, this paves the way to a fully global assessment of site-specific spatial representativeness.


\(^1\)Institute for Atmospheric and Climate Science, ETH Zurich, Switzerland

\(^2\)Department of Physics, University of Girona, Spain

\(^3\)Instituto Pirenaico de Ecologia, Consejo Superior de Investigaciones Cientificas (IPE-CSIC), Zaragoza, Spain
4.1 Introduction

The present study is part of a project that aims at estimating atmospheric solar absorption through the combination of ground-based and satellite-derived datasets as recently done for Europe [Hakuba et al., 2014a]. Within this project, special emphasis is placed upon the spatial [Hakuba et al., 2013b] and temporal [Hakuba et al., 2013a] quality assessment of the ground-based surface solar radiation (SSR) records. In addition, these records, taken from the Baseline Surface Radiation Network (BSRN, [Ohmura et al., 1998; König-Langlo et al., 2013]) and the Global Energy Balance Archive (GEBA, [Ohmura et al., 1989; Gilgen et al., 1998]) are often used to validate absolute values of gridded data products originating from climate models or satellite retrievals [e.g., Wild et al., 1998; Pinker et al., 2005; Hatzianastassiou et al., 2005; Bodas-Salcedo et al., 2008; Hinkelmann et al., 2009; Freidenreich and Ramaswamy, 2011; Sanchez-Lorenzo et al., 2013]. A main limitation in both these applications arises from the difficulty of directly comparing point observations with spatially averaged data. Hence, satellite-derived data and model deviations from ground-based observations may partly be due to the possible lack of spatial representativeness of the observation sites [e.g., Li et al., 1995, 2005]. Evidently, an assessment of the spatial representativeness of globally distributed surface sites is needed, as postulated by various studies [e.g., Dutton et al., 2006; Wild et al., 2009; Zhang et al., 2010b; Kato et al., 2012].

Hakuba et al. [2013b] studied the spatial representativeness of European SSR sites using high-resolution (0.03°) Meteosat-derived SSR data as provided by the Satellite Application Facility on Climate Monitoring (CM SAF, [Posselt et al., 2011a]). Here we extend these analyses to the entire Meteosat disk, covering, in addition to Europe, all of Africa and large parts of the Middle East and South America, to investigate the subgrid variability in different climate regimes.

The spatial representativeness of a surface site greatly depends on the time scale considered – hours, days, months – as temporal averaging strongly reduces the mismatch between point observation and surrounding area mean [e.g., Zhang et al., 2010b; Wang et al., 2012; Hakuba et al., 2013b]. Spatial variability in SSR on the subgrid scale is mainly caused by variability in cloud cover and cloud type [e.g., Long and Ackermann, 1995; Barnett et al., 1998], as well as altitude, local topography, and surface characteristics surrounding the site [e.g., Hay, 1984; Tovar et al., 1995; Riihimaki and Long, 2014]. The use of multiple sites to approximate a grid cell mean substantially enhances the spatial representativeness [e.g., Barnett et al., 1998; Li et al., 2005; Journée et al., 2012; Hakuba et al., 2013b], but is hardly feasible in most parts of the world due to insufficient coverage by surface sites.

One way to study the spatial representativeness of ground observations is the analysis of small-scale spatial variability in high-resolution satellite products [e.g., Zelenka et al., 1999; Li et al., 2005; Journée et al., 2012; Hakuba et al., 2013b], a method we take up again in the present study, thereby focusing on spatial and temporal scales widely used in energy budget studies [e.g., Stephens et al., 2012; Wild et al., 2013] or in the validation of climate models [e.g., Wild et al., 1995, 2005]. Data and methods used in this study are presented in Section 4.2. In section 4.3, we analyze the annual and seasonal mean subgrid variability in standard grids of 1° and 3° resolution and study the impact of the underlying dataset’s spatial resolution on our findings by aggregating the Meteosat data (0.03°) to coarser resolutions. Moreover, we assess the spatial representativeness of 22 surface site locations from the BSRN and 865 site locations from the GEBA, all located within the study domain, with respect to site-centered surroundings ranging from 0.25° to 3° grid cell size. Finally, we examine the statistical relationship between
subgrid variability and point representativeness. In section 4.4, we summarize the results and present our conclusions.

### 4.2 Data and Methods

Following *Hakuba et al.* [2013b], we make extensive use of the high-resolution (0.03°) SSR data record (1983-2005) derived from the MVIRI (Visible and Infrared Imager) instruments on-board the Meteosat First Generation (MFG) satellites (Meteosats 2 to 7) by the CM SAF ([www.cmsaf.eu](http://www.cmsaf.eu), [Schmetz et al., 2002; Schulz et al., 2009]). Compared to ground-based measurements (BSRN [Posselt et al., 2011b], GEBA [Sanchez-Lorenzo et al., 2013]) and CERES EBAF [Kato et al., 2013], the CM SAF dataset slightly overestimates SSR by around 6-8 Wm⁻². For more details about the dataset and its accuracy, we refer to *Mueller et al.* [2011] and *Posselt et al.* [2011a, 2012].

In the present work, we use a 5-year climatology (2001–2005) and refer to it as “cmsaf03”. For the most part, the analyses are based on the all-sky SSR data record. Occasionally, we use the clear-sky record to estimate the meridional gradient in SSR under cloud-free conditions as described in the last paragraph of this section.

The spatial domain corresponds to the field-of-view of the Meteosat satellite as shown in Figure 4.1, comprising most of Europe, the Middle East, Africa, and parts of South America between -70° to 70° East and -70° to 70° North. The number of surface sites with sufficient data to validate the spatial variability in the cmsaf03 dataset is scarce over most regions covered by the Meteosat disk. Nevertheless, the validation over Europe [*Hakuba et al.* 2013b], a region with locally rather high spatial variability in SSR (see section 4.3.1), showed good agreement and justifies the use of the dataset also over other regions.

We study the subgrid variability in two equal-angle grids of 1° and 3° resolution (Section 4.3.1). The 1° grid as utilized by, e.g., the Clouds and Earth’s Radiative Energy System (CERES) [*Wielicki et al.*, 1996] is comparable to the spectral resolution T106 as widely used for General Circulation Model (GCM) integrations. The grid of 3° resolution is comparable to the spectral resolution T42 and exemplifies coarser grids as utilized by, e.g., the International Satellite Cloud Climatology Project (ISCCP, [*Schiffer and Rossow*, 1983]) and many climate models.

In section 4.3.3, we study the spatial representativeness of surface sites from the BSRN [Ohmura et al., 1998; König-Langlo et al., 2013] and the GEBA [Ohmura et al., 1989; Gilgen et al., 1998]. For BSRN-type pyranometer measurements, the GEWEX Radiative Flux Assessment (RFA) [*Dutton and Long*, 2012] reports operational uncertainties (95% inclusion ranges) of on average ±8 Wm⁻² for monthly mean and ±6 Wm⁻² for yearly mean values. Table 4.1 provides a list of the 22 BSRN sites studied here with their locations shown in Figure 4.1. The relative random error of pyranometer measurements as stored in the GEBA is estimated at 5% of monthly means and 2% of yearly means [Gilgen et al., 1998]. In Figure 4.1, we indicate the location of the 865 sites studied here by black dots. Note that we do not use the in-situ measurements themselves to study the sites’ spatial representativeness, but their collocated cmsaf03 records as surrogates. It is hence just the location of the sites we take from the observational archives.

Following *Hakuba et al.* [2013b], we use the mean absolute deviation (MAD) as defined in equation 4.1 to measure the spatial variability of the cmsaf03 SSR data points (xᵢ) within a given area, i.e., larger-scale grid cell. The size of this area (grid cell) determines the number of
Figure 4.1: Cmsaf03 multi annual mean (2001–2005) SSR over the full Meteosat disk (Wm\(^{-2}\)). The location of 22 BSRN sites is indicated by thick pink dots and labeled (see Table 4.1). The 865 GEBA sites are indicated by fine black dots and unlabeled.

cmsaf03 data points \((n)\) contained in it. The relative mean absolute deviation (RMAD, equation 4.2) gives the spatial variability relative to the area mean \((\bar{x})\) in %.

\[
MAD = \frac{1}{n} \sum_{i=1}^{n} |x_i - \bar{x}|, \quad \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \quad (4.1)
\]

\[
RMAD = \frac{MAD}{\bar{x}} \cdot 100 \quad (4.2)
\]

The spatial sampling error (SSE, equation 4.3) of a point measurement with respect to its larger surrounding is defined as the difference between a surface site’s collocated cmsaf03 point value \(x_s\) and the surrounding area mean \((\bar{x})\) in Wm\(^{-2}\). Furthermore, SSE can be expressed relative to the single data point’s value in % (RSSE, equation 4.4). The random error caused by the comparison of a grid cell with a point measurement is represented by the station-average of the absolute (non-negative) errors, referred to as |SSE| and |RSSE|.

\[
SSE = x_s - \bar{x}, \quad x_s = \text{point value} \quad (4.3)
\]

\[
RSSE = \frac{SSE}{x_s} \cdot 100 \quad (4.4)
\]

It is important to note that part of the MAD as computed from equation 4.4 stems merely from the essentially astronomically induced latitudinal gradient in SSR, referred to as clear-sky latitude effect by Hakuba et al. [2013b]. This effect was estimated at around 3.6 Wm\(^{-2}\)deg\(^{-1}\) over Europe, largely representative of the mid-latitudes, but decreases significantly towards the equator. Hence, the contribution of this latitude effect to subgrid variability differs between
4.3 Results

4.3.1 Subgrid variability on 1° and 3° grids

We quantify the subgrid variability in SSR by means of MAD and RMAD in the climatological annual mean (2001–2005), boreal winter (DJF), and summer (JJA). Figure 4.2 depicts the annual mean RMAD (latitude effect eliminated) in the example grids of 1° (left) and 3° (right) resolution over the entire Meteosat disk. Like in Europe, grid cells of 1° resolution with RMAD exceeding 3% are mostly located in mountainous and coastal regions. The MAD (RMAD) averaged over the entire Meteosat disk is 1.4 Wm$^{-2}$ (0.8%). Considering only the land masses, the MAD (RMAD) increases to 2.3 Wm$^{-2}$ (1.1%), which is slightly lower than the 2.4 Wm$^{-2}$ (1.6%) over Europe only [Hakuba et al., 2013b]. 90% of all grid cells over land do not exceed a MAD (RMAD) of 5.0 Wm$^{-2}$ (2.4%), again similar to Europe only. Not removing the latitude effect has only marginal influence (around +0.1 Wm$^{-2}$ or +0.1%, respectively) on these averages.

The MAD (RMAD) in the coarser grid of 3° resolution almost doubles to on average 4.1 Wm$^{-2}$ (1.9%) over land and 10% of all grid cells exceed 8.2 Wm$^{-2}$ (3.9%). Here, the latitude effect is more relevant and would additionally increase the land average by +0.5 Wm$^{-2}$ or +0.3%, respectively. This effect is most distinct at higher latitudes beyond 30° North, with an increase of twice as much. The location and spatial extent of the high-variability spots as seen in the 1° grid is not substantially altered in the 3° grid.

From the histograms in Figure 4.2, we see that the fractional amount (%) of grid cells with RMAD exceeding 1% is larger over Europe land (light blue) than over the entire Meteosat disk (dark blue). In both grids, South America and Africa show comparably little structure in variability over wide areas. For example in deserts (e.g. Sahara, Arabian Peninsula) and equatorial rainforests (unless mountainous) the subgrid variability is similar to or even lower than in Central Europe, which was referred to as low-variability region in Hakuba et al. [2013b].

The high-variability regions, situated in or near mountainous landscapes, are of similar magnitude all over the Meteosat disk. Within the frame of the dataset used here, there are multiple lines of evidence pointing at persistent cloud features to be their major cause. First, we find that the high-variability spots essentially vanish under cloud-free conditions (not shown). As compared to the all-sky case, the clear-sky MAD averaged over land is substantially reduced by on average 70%. This reduction is even more pronounced (85%) in grid cells with high variability (RMAD > 3%) under all-sky conditions. Secondly, we compute SSR anomalies with respect to their zonal means in each latitude band and see that the clear-sky SSR is slightly enhanced over elevated terrain, whilst the all-sky SSR is predominantly decreased (not shown), again pointing to clouds as the major source of subgrid variability in this dataset. Persistent gradients in cloud cover, on local scales relevant for the climatological subgrid vari-
ability as defined here, are often orographically induced or amplified [e.g., Wulfmeyer et al., 2011; Hakuba et al., 2012], which is in line with our findings. It is, however, important to note that the retrieval of the cmsaf03 dataset partially uses coarser horizontal resolutions than the 0.03°, especially regarding the input data such as total water vapor [e.g., Müller et al., 2009]. Thus, small-scale variations in clear-sky SSR due to changes in altitude are likely underestimated.

Since Hakuba et al. [2013b] discussed the seasonal differences in MAD and RMAD over Europe, we focus here on the (sub-) tropical regions (Figure 4.3). Over Africa, regional contrasts in RMAD arise mostly from the seasonal shift in the ITCZ. To roughly outline the location of the ITCZ in JJA and DJF, we show the 5-year mean surface cloud radiative forcing (CRF = all-sky minus clear-sky SSR) over the Meteosat disk between -40° and 30° North (Figure 4.3, top panels) together with the corresponding RMAD fields (lower panels). In accordance with the CRF minima in JJA, RMAD is most pronounced over Sub-Saharan Africa between 0° to 15° North. RMAD maxima are located along the West coast and mountainous regions of Eastern Africa. Apart from these mountainous regions, Northern Africa is characterized by low variability during DJF and the subgrid variability is enhanced South of the equator. A similar signal is visible over South America, where high variability occurs in the Brazilian Highlands (JJA) and at the south-eastern coast near the Tropic of Capricorn (23° South). The parts of the Andes as covered by the Meteosat domain are characterized by high RMAD year-round. Although reduced in magnitude, the annual mean captures all these high-variability spots.

Enhanced RMAD related to the CRF minima in Madagascar, Northeastern Brazil, and the West coast of Southern Africa (Figure 4.3) might also be linked to other characteristic weather
patterns such as the trade wind easterlies and their interaction with orography ([Nassor and Jury, 1998; Chung, 1982]) as well as the formation of marine stratocumuli [Wood, 2012].

4.3.2 Resolution dependency

To our knowledge, a global satellite-derived SSR dataset of equally high spatial resolution as the cmsaf03 (0.03°) is not available. To extend the present analysis beyond the Meteosat disk to the full global scale, one would need to use a dataset of coarser resolution such as for example the CLARA-A1 product (CM SAF, [Karlsson et al., 2013; Riihelä et al., 2013]) with 0.25° grid spacing or the CERES CRS dataset that provides irradiances on the scale of ~30 km footprints [Rose et al., 2013].

Although we do not directly use any of these data in the present study, we investigate whether a resolution of 0.25° yields similar results, as derived here based on the 0.03° cmsaf03 dataset, and could be used for further analysis on the global scale. From a statistical perspective, we expect a reduction in spatial variability due to the coarser resolution, which we quantify here.

We aggregate the 0.03° cmsaf03 data over the Meteosat disk to an equal-angle grid of 0.25° resolution. Based on this coarser dataset, we again compute MAD (RMAD) in the 1° grid, and subtract the resulting map from the results above obtained with the original cmsaf03 dataset (not shown). Considering only the land masses, a mean bias of 0.3 Wm⁻² (0.15%) is found. This is equivalent to a decrease in subgrid variability by around 13% relative to the Meteosat land mean MAD of 2.4 Wm⁻² computed with the 0.03° cmsaf03 data (see previous Section, latitude effect not eliminated). Qualitatively, the maps of MAD (RMAD) based on either the original cmsaf03 or the aggregated one, are in good agreement, indicating the same high-variability regions. Furthermore, the relative biases between the maps are not system-
attractively larger in regions of large MAD (RMAD). Hence, a dataset of 0.25° resolution could equally be used to depict the subgrid variability on a 1° grid, keeping in mind the slight systematic underestimation.

We repeat the above analysis using different aggregated resolutions between 0.03° and 0.45° (see Figure 4.4) to again obtain RMAD in the 1° grid. A linear relationship between RMAD and the grid resolution (degree) is evident, suggesting a relative reduction in subgrid variability by 5% per 0.1° increase in grid spacing. By contrast, starting from a field with random spatial structure (white-noise process) yields an inversely proportional relationship (Figure 4.4, blue line), which is in line with results by Collins and Woodcock [1999] who studied the resolution-dependent variance in remotely sensed images. In a dataset with non-random spatial structure, such as the cmsaf03, nearby values are highly correlated, hence, there is less variability within an aggregated pixel than between them [Collins and Woodcock, 1999]. As a result, the variability decreases more slowly with resolution than in the random case. In this sense, a much coarser dataset of up to 0.5° could still reproduce 75% of the average RMAD (Meteosat disk land) as computed with the original cmsaf03 dataset of 0.03° resolution.

4.3.3 Point representativeness

BSRN and GEBA

We compute the site-centered and, hence, grid-independent spatial sampling error of a surface site (SSE, RSSE) by assuming its collocated cmsaf03 pixel is the center of a larger grid cell of variable size. Compared to Hakuba et al. [2013b], who estimated this for 9 BSRN and 134 GEBA sites in Europe, we now compute the SSE and RSSE at 22 BSRN and 865 GEBA sites as contained by the Meteosat disk. In Figure 4.5, we show the |RSSE| as a function of grid cell size (0.03° to 3°) at the BSRN sites (in color) together with the mean and median curves based on the GEBA sample (black solid and black dashed). Table 4.1 presents the BSRN sites’
### Table 4.1: BSRN sites’ site-centered SSE ($\text{Wm}^{-2}$) and RSSE (\%, in brackets) with respect to their larger surroundings of 0.25°, 0.5°, 1°, 2°, and 3° grid cell size.

<table>
<thead>
<tr>
<th>BSRN site</th>
<th>label</th>
<th>0.25°</th>
<th>0.5°</th>
<th>1°</th>
<th>2°</th>
<th>3°</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bermuda</td>
<td>BER</td>
<td>1.7 (0.9)</td>
<td>2.4 (1.3)</td>
<td>2.7 (1.4)</td>
<td>2.8 (1.5)</td>
<td>2.7 (1.4)</td>
</tr>
<tr>
<td>Brasilia</td>
<td>BRB</td>
<td>1.0 (0.4)</td>
<td>1.2 (0.5)</td>
<td>0.8 (0.3)</td>
<td>0.5 (0.2)</td>
<td>0.1 (0.1)</td>
</tr>
<tr>
<td>Cabauw</td>
<td>CAB</td>
<td>0.0 (0.0)</td>
<td>0.7 (0.6)</td>
<td>1.0 (0.8)</td>
<td>0.8 (0.6)</td>
<td>0.7 (0.5)</td>
</tr>
<tr>
<td>Camborne</td>
<td>CAM</td>
<td>-1.4 (-1.0)</td>
<td>-2.0 (-1.5)</td>
<td>-2.3 (-1.8)</td>
<td>-2.5 (-1.9)</td>
<td>-2.6 (-2.0)</td>
</tr>
<tr>
<td>Carpentras</td>
<td>CAR</td>
<td>0.1 (0.1)</td>
<td>1.6 (0.8)</td>
<td>4.7 (2.5)</td>
<td>10.7 (5.6)</td>
<td>14.8 (7.8)</td>
</tr>
<tr>
<td>Cener</td>
<td>CNR</td>
<td>1.9 (1.1)</td>
<td>3.8 (2.2)</td>
<td>2.1 (1.2)</td>
<td>-2.3 (-1.4)</td>
<td>-4.0 (-2.4)</td>
</tr>
<tr>
<td>De Aar</td>
<td>DAA</td>
<td>-0.3 (-0.1)</td>
<td>-0.0 (-0.0)</td>
<td>0.4 (0.2)</td>
<td>1.5 (0.6)</td>
<td>3.2 (1.3)</td>
</tr>
<tr>
<td>Florianopolis</td>
<td>FLO</td>
<td>-2.4 (-1.3)</td>
<td>-1.1 (-0.6)</td>
<td>1.1 (0.6)</td>
<td>0.8 (0.4)</td>
<td>0.2 (0.1)</td>
</tr>
<tr>
<td>Gobabeb</td>
<td>GOB</td>
<td>-0.2 (-0.1)</td>
<td>0.0 (0.0)</td>
<td>1.1 (0.4)</td>
<td>14.8 (5.3)</td>
<td>21.2 (7.6)</td>
</tr>
<tr>
<td>Ilorin</td>
<td>ILO</td>
<td>-0.7 (-0.3)</td>
<td>-0.6 (-0.3)</td>
<td>0.1 (0.0)</td>
<td>0.8 (0.3)</td>
<td>1.1 (0.5)</td>
</tr>
<tr>
<td>Izaña</td>
<td>IZA</td>
<td>0.3 (0.1)</td>
<td>3.0 (1.2)</td>
<td>5.0 (2.1)</td>
<td>3.3 (1.4)</td>
<td>2.2 (0.9)</td>
</tr>
<tr>
<td>Lerwick</td>
<td>LER</td>
<td>2.4 (2.3)</td>
<td>3.4 (3.3)</td>
<td>4.0 (3.8)</td>
<td>4.1 (3.9)</td>
<td>3.8 (3.7)</td>
</tr>
<tr>
<td>Lindenberg</td>
<td>LIN</td>
<td>-0.4 (-0.3)</td>
<td>-0.6 (-0.5)</td>
<td>-0.6 (-0.5)</td>
<td>-0.2 (-0.1)</td>
<td>0.0 (0.0)</td>
</tr>
<tr>
<td>Palaiseau</td>
<td>PAL</td>
<td>-0.3 (-0.2)</td>
<td>-0.3 (-0.2)</td>
<td>-0.7 (-0.5)</td>
<td>-0.8 (-0.6)</td>
<td>-0.7 (-0.5)</td>
</tr>
<tr>
<td>Payerne</td>
<td>PAY</td>
<td>1.6 (1.1)</td>
<td>3.4 (2.3)</td>
<td>5.8 (3.8)</td>
<td>5.7 (3.8)</td>
<td>5.5 (3.6)</td>
</tr>
<tr>
<td>Petrolina</td>
<td>PTR</td>
<td>0.7 (0.3)</td>
<td>0.7 (0.3)</td>
<td>0.0 (0.0)</td>
<td>-1.1 (-0.4)</td>
<td>-1.2 (-0.5)</td>
</tr>
<tr>
<td>Rolim de Moura</td>
<td>RLM</td>
<td>0.1 (0.1)</td>
<td>0.5 (0.2)</td>
<td>1.0 (0.5)</td>
<td>2.6 (1.2)</td>
<td>3.1 (1.4)</td>
</tr>
<tr>
<td>Sede Boquer</td>
<td>SBO</td>
<td>-0.9 (-0.4)</td>
<td>-1.6 (-0.7)</td>
<td>-2.3 (-0.9)</td>
<td>-1.6 (-0.7)</td>
<td>-2.3 (-0.9)</td>
</tr>
<tr>
<td>São Martinho da Serra</td>
<td>SMS</td>
<td>0.8 (0.4)</td>
<td>1.0 (0.5)</td>
<td>0.1 (0.1)</td>
<td>-1.2 (-0.6)</td>
<td>-1.4 (-0.8)</td>
</tr>
<tr>
<td>Solar Village</td>
<td>SOV</td>
<td>0.1 (0.1)</td>
<td>0.4 (0.1)</td>
<td>1.5 (0.6)</td>
<td>1.9 (0.7)</td>
<td>1.7 (0.6)</td>
</tr>
<tr>
<td>Tamanrasset</td>
<td>TAM</td>
<td>0.4 (0.1)</td>
<td>0.4 (0.1)</td>
<td>0.1 (0.0)</td>
<td>-1.5 (-0.6)</td>
<td>-2.8 (-1.0)</td>
</tr>
<tr>
<td>Toravere</td>
<td>TOR</td>
<td>-0.0 (-0.0)</td>
<td>0.3 (0.2)</td>
<td>0.3 (0.3)</td>
<td>0.5 (0.4)</td>
<td>0.3 (0.3)</td>
</tr>
</tbody>
</table>

*For comparison purposes: Here, the table header refers to the grid cell size in terms of the cell’s full edge length in degree. In Hakuba et al. [2013b], the numbers in the table header referred to the half width of the grid cell. For example, column 0.5° in Hakuba et al. [2013b] corresponds to column 1° in the present paper.

SSE and RSSE with respect to 0.25°, 0.5°, 1°, 2°, and 3° surroundings or site-centered grid cells, respectively. Table 4.2 summarizes the GEBA dataset’s statistics of SSE and RSSE for the same range of “grid” resolutions, covering the resolution of many modeling and satellite-derived datasets available.

Considering the BSRN dataset, two sites, Carpentras in Europe and Gobabeb in Africa, show strongly rising |RSSE| (|SSE|) with distance, reaching up to 8% (15 and 21 Wm$^{-2}$) with respect to a 3° surrounding (Figure 4.5). On the other hand, at sites located in regions with no strong SSR variability, the curves stay rather flat (e.g., Lindenberg, Ilorin, Toravere, Petrolina). In addition, as in Hakuba et al. [2013b], some curves, as well as the GEBA mean and median functions, show a steeper increase in |RSSE| at smaller distances and a leveling-off thereafter. Often, these curves belong to sites that lie in regions of large small-scale variability, e.g., in or near mountain ranges or near coast lines (e.g., Payerne, Lerwick, Bermuda). At some other sites, the |RSSE| rises at smaller distances but declines again with respect to a larger surrounding (e.g., Izaña, Cener, Florianopolis). Hence, these sites are more representative of a larger grid cell than for their immediate surrounding. This might arise from an isolated anomaly in SSR in the site’s vicinity that diminishes in a larger-scale surrounding. For example, the island site at Izaña appears to be more representative of the surrounding ocean in a larger grid cell than for the local meteorological conditions over the island interior. A second example is Florianopolis, a coastal site located offshore Brazil that also exhibits larger |RSSE| for its closer surrounding. But unlike Izaña, the grid cell increasingly captures an offsetting land-sea contrast the larger it grows.
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Table 4.2: Statistics of GEBA sites’ site-centered SSE (Wm$^{-2}$) and RSSE (%), in brackets) with respect to their larger surroundings of 0.25°, 0.5°, 1°, 2°, and 3° grid cell size. Statistics are based on 865 GEBA sites. With respect to all grid cell sizes, the GEBA site Mount Kenya has the highest |RSSE| (last row).

<table>
<thead>
<tr>
<th>GEBA SSE &amp; RSSE</th>
<th>0.25°</th>
<th>0.5°</th>
<th>1°</th>
<th>2°</th>
<th>3°</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>0.2 (0.1)</td>
<td>0.4 (0.2)</td>
<td>0.5 (0.2)</td>
<td>0.3 (0.1)</td>
<td>-0.1 (-0.1)</td>
</tr>
<tr>
<td>abs. mean</td>
<td>1.0 (0.5)</td>
<td>1.8 (1.0)</td>
<td>2.7 (1.5)</td>
<td>3.6 (2.0)</td>
<td>4.1 (2.3)</td>
</tr>
<tr>
<td>median</td>
<td>0.2 (0.1)</td>
<td>0.4 (0.2)</td>
<td>0.6 (0.3)</td>
<td>0.6 (0.3)</td>
<td>0.5 (0.3)</td>
</tr>
<tr>
<td>abs. median</td>
<td>0.5 (0.3)</td>
<td>1.0 (0.6)</td>
<td>1.8 (1.0)</td>
<td>2.3 (1.3)</td>
<td>2.7 (1.5)</td>
</tr>
<tr>
<td>σ</td>
<td>1.6 (0.9)</td>
<td>2.8 (1.5)</td>
<td>4.1 (2.3)</td>
<td>5.4 (2.9)</td>
<td>6.1 (3.3)</td>
</tr>
<tr>
<td>abs. max</td>
<td>16.7 (8.7)</td>
<td>31.3 (16.2)</td>
<td>49.1 (25.5)</td>
<td>59.5 (31.0)</td>
<td>63.0 (32.7)</td>
</tr>
</tbody>
</table>

*For comparison purposes: Here, the table header refers to the grid cell size in terms of the cell’s full edge length in degree. In Hakuba et al. [2013b], the numbers in the table header referred to the half width of the grid cell. For example, column 0.5° in Hakuba et al. [2013b] corresponds to column 1° in the present paper.

As for Europe [Hakuba et al., 2013b], when averaging over the large GEBA dataset, the SSE (RSSE) almost cancel out with mean values well below ±0.5 Wm$^{-2}$ (±0.2%), considering all surroundings of up to 3° grid cell size (Table 4.2). The mean |SSE| (|RSSE|) with respect to a 1° surrounding is around 3 Wm$^{-2}$ (1-2%) and increases slightly to about 4 Wm$^{-2}$ (2-3%) with respect to a 3° grid cell. The site Mount Kenya represents an outlier, showing exceptionally large |RSSE| of up to 30% (3°, table 4.2). With its conical shape, Mount Kenya embodies an extreme peak (5200 m), surrounded by flat savanna and shrub lands. We believe the substantial topographic variations and associated variability in cloud cover are responsible for its very limited spatial representativeness.

Around 60% of all GEBA sites have |RSSE| of 2% or lower with respect to a 3° grid cell, and hence could be considered representative within the range of in-situ measurement uncertainty (Section 4.2). For 1° grid cells, around 75% of all sites have |RSSE| lower than 2%. A geographical summary of our findings is given in Figure 4.6, indicating the location of the BSRN and GEBA sites together with their |RSSE| (in color) with respect to a site-centered 1° grid cell. Blueish colors refer to |RSSE| smaller than 2%. Orange colors indicate sites with |RSSE| larger than 3%, the upper limit of site representativeness as discussed in the following section.

Upper & Lower Limits of representativeness

To quantify lower and upper limits for site representativeness, we examine two regions in Africa that distinguish themselves by particularly low and high RMAD, respectively: the Saharan region, where RMAD rarely exceeds 1% (15° to 28° North, -5° to 20° East) and a region comprising parts of Ethiopia and Kenya (2° to 12° North, 35° to 40° East), where RMAD exceeds 6%. These regions are indicated by blue rectangles in Figure 4.2 (left). From both these regions, we arbitrarily select 300 points and compute the |RSSE| for their larger surroundings of up to 3° grid cell size as done above for the BSRN and GEBA sites. With respect to the 1° (3°) surrounding, the Saharan |RSSE| are on average 0.2% (0.3%). In Ethiopia, the mean |RSSE| is about 3% (5%), thus, ten times larger.

The |RSSE| computed from the Saharan region are likely a rarity over other, not desert-like regions. Likewise, the |RSSE| in mountainous regions represent an upper limit to site representativeness. Indeed, around 85% of the GEBA sites do not exceed |RSSE| of 3% (5%) with respect to a 1° (3°) surrounding. By contrast, most of the GEBA sites (85%) have larger
Figure 4.5: RSSE (y axis, %) as a function of surrounding area size (x axis, in degree) based on the "cnsaf03" data at 22 BSRN sites (colors) and the GEA sample (865 sites) mean (black solid) and median (black dashed). See text for details. The area size refers to the surrounding grid cell’s full width. Note: in Hakuba et al. [2013b], the area size referred to the half-width size of a grid cell.

RSSE than the Saharan points. However, on the level of an individual site almost anything is possible as the concrete example of Mount Kenya shows.

### 4.3.4 Subgrid variability versus point representativeness

Having looked at the grid-specific subgrid variability (RMAD) and site-specific point representativeness (RSSE) separately, we now examine their relationship to see whether the RMAD (Figure 4.2) can serve as a proxy for the RSSE. Provided the RMAD represents a useful proxy for the site-specific RSSE, one can deduce the representativeness of any site that is located within the Meteosat disk from the maps in Figure 4.2. In the following, the RSSE either refers to a site-centered 1° surrounding as introduced in Section 4.3.3 or to the site’s collocated 1° grid cell in the standard grid used in Section 4.3.1 and Figure 4.2 (left) to compute RMAD. This grid-specific RSSE tells us how representative a surface site is of the mean of a grid cell in a given grid [Hakuba et al., 2013b].

The correlation (r) between the GEA sites’ annual mean site-centered RSSE and their collocated grid cells’ RMAD (5-year average) is at 0.55 not particularly high (Figure 4.7, left). However, it is worthwhile to explore their relationship more thoroughly. The majority of sites (67%) have site-centered RSSE smaller than the RMAD would suggest, hence lie below the 1:1 line (dashed black line). The red triangles in Figure 4.7 indicate the RMAD means of five equally sized (1%) bins between 0% and 5% (x axis) and their corresponding RSSE percentile value (median, 75th and 90th, y axis). The median trace and 75th percentiles are again indicative for an overestimation of the site-centered RSSE via the RMAD.

Considering the grid-specific RSSE (r = 0.6) as shown in Figure 4.7 (right), the RMAD bin means are now more indicative for the binned median RSSE. Also, both, the 75th and 90th percentiles are enhanced compared to the site-centered case and point to an increased spread in grid-specific RSSE with increasing RMAD. Since a site is likely shifted northerly or southerly with respect to the grid cell center in a fixed grid (latitude effect), the grid-specific RSSE are on average +0.5% larger than the site-centered RSSE (r = 0.75, not shown). Hence, the
Figure 4.6: Site-centered $|\text{RSSE}|$ (%) with respect to a 1° surrounding at 22 BSRN sites (thick dots, labeled) and 865 GEBA sites (smaller dots, unlabeled). Blueish colors indicate $|\text{RSSE}| < 2\%$, orange/red colors indicate $|\text{RSSE}| > 3\%$.

statistical relationship between RMAD and $|\text{RSSE}|$ differs slightly between the site-centered and grid-specific case, the latter being more conservative.

Instead of considering the single bins, we now look at upper limits of RMAD. The yellow and orange shadings in Figure 4.7 illustrate the $|\text{RSSE}|$ (y axis) associated with a certain maximum RMAD (x axis) that 90% of the sites do not exceed. For example, 90% of the sites located in grid cells with up to 2% RMAD have site-centered $|\text{RSSE}|$ of around 2% or lower, hence, could be considered representative within in-situ measurement uncertainty (Figure 4.7, left). In the same sense, it is very likely that in grid cells with up to 3% RMAD a site’s $|\text{RSSE}|$ is below 3%. For the grid-specific $|\text{RSSE}|$ a slightly different rule of thumb applies (at least for RMAD up to 3%): With 90% probability, the grid-specific $|\text{RSSE}|$ is not higher than the RMAD plus 1% (Figure 4.7, right).

With this relationship in view, one can deduce both, the site-centered and grid-specific $|\text{RSSE}|$, from the maps in Figure 4.2. Furthermore, this relationship is especially relevant, when extending the present study to the full global scale using a dataset with coarser horizontal resolution than the cm SAF03 (0.03°). Such a coarser dataset, e.g. with 0.25° horizontal resolution, captures the site location insufficiently, hence, cannot be used to determine the site-specific RSSE. However, as we showed in Section 4.3.2, the drop in RMAD with decreasing grid resolution is not as crucial. Thus, keeping in mind the systematic underestimation as illustrated in Figure 4.4, the RMAD based on a coarser dataset could serve as a proxy to the $|\text{RSSE}|$ of surface sites outside the Meteosat disk.
4.4 Discussion and Conclusions

In the present work, we spatially extended our previous analyses over Europe [Hakuba et al., 2013b] to the full Meteosat disk, studying the subgrid variability (MAD, RMAD) of annual and seasonal mean (2001–2005) surface solar radiation (SSR) on 1° and 3° standard grids as well as the spatial representativeness (SSE, RSSE) of 887 surface sites from the Baseline Surface Radiation Network (BSRN) and the Global Energy Balance Archive (GEBA), using high-resolution (0.03°) SSR data from the Satellite Application Facility on Climate Monitoring (CM SAF). Covering not only Europe, but all of Africa and large parts of the Middle East and South America, the Meteosat disk contains additional climate-relevant features that are similar to the ones in Europe, e.g., mountain ranges, coastlines, and comparably flat terrain, but also very different ones, such as deserts, rainforests, and the seasonally changing location of the ITCZ. This allows placing the previous results over Europe into a larger perspective.

We focused on spatial and temporal resolutions widely used in energy budget studies [e.g., Stephens et al., 2012] or the validation of climate models [e.g., Wild et al., 1995, 2005]. The present setup based on climatological seasonal and annual means allows the study of spatial subgrid variability in SSR caused by persistent gradients in cloud cover that seem primarily induced or amplified by elevated topography [Wulfmeyer et al., 2011] as well as by land-sea contrasts [Wood, 2012] and convective activities related to the ITCZ. Considering daily to sub-daily timescales would drastically increase the spatial variability in SSR, which is strongly reduced by the temporal averaging [e.g., Wang et al., 2012].

Averaged over the entire Meteosat disk (only land), the subgrid variability (MAD, RMAD) in the 1° standard grid is with 2.4 Wm⁻² (1.2%) slightly lower than over Europe only [Hakuba et al., 2013b]. Spots of high annual mean RMAD exceeding 3% are particularly located in mountainous and coastal regions and are of similar magnitude on all continents studied here.
In the coarser grid of 3° resolution, the location of the high-variability regions is not particularly altered, but their magnitude almost doubles.

Looking at different seasons, changes in location and magnitude of the high-variability spots are particularly evident in (sub-)tropical regions. In accordance with the shifting location of the ITCZ the variability is enhanced during the wet season. Still, the highest variability prevails around the African mountains and at the west coast of Southern Africa. Over deserts and rainforest the subgrid variability in SSR is similar to or even lower than in Central Europe, identified as low-variability region in Hakuba et al. [2013b].

We assessed the spatial representativeness of 22 BSRN and 865 GEBA sites by means of the (relative) spatial sampling error (RSSE, SSE). The absolute mean value of these errors is around 1-3 Wm\(^{-2}\) (1-2%) with respect to a 1° surrounding grid cell and 4-5 Wm\(^{-2}\) (2-3%) with respect to a 3° grid cell, which is in good agreement with the study over Europe [Hakuba et al., 2013b]. This error magnitude is on the order of the measurement uncertainty associated with SSR observations in the GEBA (2% of yearly means, [Gilgen et al., 1998]). In fact, the majority of surface sites (75%) have absolute RSSE smaller than this measurement uncertainty. Averaging over a sufficiently large set of surface sites as used here and over Europe [Hakuba et al., 2013b], the (positive and negative) SSE (RSSE) cancel out, remaining well below ±0.5 Wm\(^{-2}\) (±0.2%) and, hence, would not substantially affect the computation of a regional mean based on these point measurements [Hakuba et al., 2014a].

We further showed that the subgrid variability (RMAD) with respect to a fixed grid can serve as an excellent proxy for site-specific representativeness. At most sites (90%), the RSSE corresponds to the RMAD of the site’s collocated grid cell, exceeding it by not more than 1%. This allows to estimate the site-specific RSSE from gridded RMAD with high reliability.

Global satellite-based SSR datasets, needed to spatially extend the present study beyond the Meteosat disk are available but only with coarser spatial resolution. The dependence of the grid-specific RMAD on the resolution of the underlying data is much weaker than expected for a dataset with random spatial structure [Collins and Woodcock, 1999]. Thus, a global assessment of RMAD beyond the Meteosat disk using a dataset of coarser horizontal resolution is feasible. In combination with the established link between RMAD and RSSE, this could also serve to approximate the spatial representativeness of surface sites outside the Meteosat disk on the full global scale.

Acknowledgments

This study is funded by the Swiss National Science Foundation grant 200021 135395 (“Towards an improved understanding of the Global Energy Balance: Absorption of solar radiation”). A. Sanchez-Lorenzo was supported by the “Secretaria per a Universitats i Recerca del Departament d’Economia i Coneixement, de la Generalitat de Catalunya i del programa Co-fund de les Accions Marie Curie del 7è Programa marc d’R+D de la Unió Europea” (2011 BP-B 00078), the postdoctoral fellowship # JCI-2012-12508, and the project NUCLERSOL (CGL2010-18546). We would like to thank Guido Müller and Stefanos Mystakidis for the maintenance of the GEBA and Christoph Schär for continuous support. Furthermore, we thank Reto Stöckli and Jörg Trentmann for useful discussions and support on data usage. The CM SAF MVIRI dataset SIS - Surface incoming shortwave radiation, version 001 is freely available for all purposes under www.cmsaf.eu.
Chapter 5

Solar Absorption over Europe from collocated surface & satellite observations
Solar Absorption over Europe from collocated surface and satellite observations

Maria Z. Hakuba¹, Doris Folini¹, Gabriela Schaepman-Strub², Martin Wild¹

Abstract

Solar radiation is the primary source of energy for the Earth’s climate system. Although the incoming and outgoing solar fluxes at the top-of-atmosphere can be quantified with high accuracy, large uncertainties still exist in the partitioning of solar absorption between surface and atmosphere. To compute best estimates of absorbed solar radiation at the surface and within the atmosphere representative for Europe during 2000–2010, we combine temporally homogeneous and spatially representative ground-based observations of surface downwelling solar radiation with collocated satellite-retrieved surface albedo and top-of-atmosphere net irradiance. We find best estimates of Europe land annual mean surface and atmospheric absorption of 117.3 ± 6 W m⁻² (41.6 ± 2% of TOA incident irradiance) and 65.0 ± 3 W m⁻² (23.0 ± 1%). The fractional atmospheric absorption of 23% represents a robust estimate largely unaffected by variations in latitude and season, thus, making it a potentially useful quantity for first order validation of regional climate models. Uncertainties of the individual absorption estimates arise mostly from the measurements themselves. In this context, the surface albedo and the ground-based solar radiation data are the most critical variables. Other sources of uncertainty, like the multiplicative combination of spatially averaged surface solar radiation and surface albedo estimates, and the spatial representativeness of the point observations, are either negligibly small or can be corrected for.


¹Institute for Atmospheric and Climate Science, ETH Zurich, Switzerland
²Institute of Evolutionary Biology and Environmental Studies, University of Zurich, Switzerland
5.1 Introduction

The incoming solar energy is the main driver of all pivotal processes on our planet. The solar radiation absorbed by the climate system regulates its thermal and dynamical conditions, the hydrological cycle, and the biosphere’s productivity [e.g., Kiehl and Trenberth, 1997; Ramathan et al., 2001; Wild et al., 2008]. Under equilibrium conditions, the net inflow of solar energy is balanced by the net outflow of longwave radiation at the top-of-atmosphere (TOA). At times of changing climate, the Earth’s energy budget is in imbalance [Hansen et al., 2005; Trenberth and Fasullo, 2010; Hansen et al., 2011; Loeb et al., 2012].

The mean-state and temporal evolution of the energy budget’s components have been investigated for almost a century, with first attempts by, e.g., Abbot and Fowle [1908], who quantified the disposition of heat in the climate system, and Dines [1917], who was the first to estimate the overall components of the heat balance. While the observational coverage has much improved since the beginning of the last century, with denser ground-based observational networks (e.g., Global Energy Balance Archive, GEBA, [Ohmura et al., 1989]) and high-accuracy satellite-based measurements, e.g., the Solar Radiation and Climate Experiment (SORCE, [Anderson and Cahalan, 2005]) and the Clouds and Earth’s Radiant Energy System (CERES [Wielicki et al., 1996; Loeb et al., 2009]), some of the budget’s components are still afflicted with large uncertainties on a global mean basis, both from an observational and modeling perspective [e.g., Hartmann et al., 1986; Ohmura and Gilgen, 1993; Pyker et al., 1995; Li et al., 1997; Kiehl and Trenberth, 1997; Wild et al., 1998; Hatzianastassiou and Vardavas, 1999; Hatzianastassiou et al., 2005; Trenberth et al., 2009; Wild, 2012; Stephens et al., 2012; Wild et al., 2013].

The recent availability of sophisticated space-borne observations (e.g., SORCE and CERES) enables a quite accurate estimate of the global energy budget at TOA [Loeb et al., 2009, 2012]. But the distribution of radiative energy within the climate system is largely uncertain, since satellite instruments cannot directly measure the surface shortwave and longwave fluxes, which have to be inferred from the measured radiances at TOA using radiative transfer models.

Large uncertainties exist especially in the disposition of solar energy. The various estimates of global mean surface and atmospheric solar absorption vary in a range of more than 20 Wm$^{-2}$, which corresponds to an uncertainty of 30% in atmospheric absorption [e.g., Abbot and Fowle, 1908; Houghton, 1954; Budyko, 1982; Ohmura and Gilgen, 1993; Kiehl and Trenberth, 1997; Li et al., 1997; Wild et al., 1998; Hatzianastassiou and Vardavas, 1999; Hatzianastassiou et al., 2005; Trenberth et al., 2009; Wild, 2012; Stephens et al., 2012; Wild et al., 2013].

Likewise, global climate models (GCM) are not able to produce consistent estimates of the disposition of solar energy within the climate system. Atmospheric and surface solar absorption of the CMIP3/IPCC-AR4 models differ within 20% and 14% of their absolute values, whereas TOA values differ only within 4% [Wild et al., 2005, 2008]. The latest intercomparison of CMIP5/IPCC-AR5 GCMs shows improved agreement with a model range of about 10 Wm$^{-2}$ or 13% of global mean atmospheric absorption [Wild et al., 2013]. Still, the GCM-simulated atmospheres appear too transparent with respect to solar irradiance [Wild et al., 1998, 2008, 2013]. The highly debated effect of anomalous cloud absorption (e.g., Stephens and Tsay [1990]; Cess et al. [1995]; Li et al. [1995]; Li [2004], and references therein) and its possible underestimation in GCMs constitutes yet another source of uncertainty.

Undoubtedly, there is still a need for improved estimates, including associated uncertainties. Addressing this need, the present study aims at estimating mean-state surface and atmospheric solar absorption under all-sky conditions relying to the extent possible on direct observations from both space and surface. This is achieved by combining ground-based surface solar radiation measurements over Europe with collocated satellite-derived surface albedo and TOA net
5.2 Data and Methods

Figure 5.1 depicts the incoming and outgoing fluxes of solar radiation at the surface and at the top-of-atmosphere (TOA), thereby illustrating the approach of combining space-born (spatial averages) and ground-based observations (point-like) to compute surface and atmospheric absorption. The data sources and their spatial resolution are indicated as well. The respective Sections 5.2.1 and 5.2.2 summarize the datasets’ specifics in more detail.

The main objective of the present study is to estimate the solar absorption in the atmosphere (ASRatm, see equation 5.1), which is the residual of the net incoming solar radiation at the top-of-atmosphere (TOAnet) and the absorption of solar radiation at the surface (ASRsrf). TOAnet is computed from the outgoing (TOAup) and incoming solar fluxes (TOAin) derived from satellite measurements at the TOA. To estimate ASRsrf, we combine surface solar radiation (SSR) data from ground-based observations with satellite-retrieved surface albedo (A) following equation 5.2.

Throughout the entire study we work with 1° area averages. The 1° grid is given by the CERES EBAF TOA product (see Section 5.2.2) and referred to as “the CERES grid” in the following. In Section 5.4, we identify and discuss two major sources of uncertainties: 1) The accuracy of the SSR, surface albedo, and TOA measurements. 2) Uncertainties that arise from combining these datasets: The spatial representativeness of the SSR point observations for their collocated 1° grid cells and the multiplicative combination of SSR with surface albedo.
Figure 5.1: Basic idea of method: Combination of satellite-derived datasets of top-of-atmosphere solar fluxes and surface albedo (area averages) with ground-based observations (point measurements) of surface solar radiation. The used datasets together with their spatial resolution are indicated as well. See respective sections for further details.

We only use observational SSR records of sufficient temporal homogeneity and adjust their spatial representativeness with respect to their collocated 1° grid cells (Section 5.2.1).

\[
ASR_{\text{atm}} = TOA_{\text{net}} - ASR_{\text{surf}} \tag{5.1}
\]

\[
ASR_{\text{surf}} = (1 - A) \cdot SSR \tag{5.2}
\]

We focus on the time period 2000–2010, and the spatial domain between -9° to 31° East and 36° to 64° North, which covers the larger part of Europe. Throughout the paper, annual means are computed from average annual cycles, to cope with the different (monthly mean) data gaps in the different datasets. We find it useful to express the absorption quantities not only in absolute units [Wm⁻²] but also as fraction of TOA incoming solar radiation (TOAin), given in % and referred to as “fractional ASRsurf” and “fractional ASRatm” in the following.

5.2.1 Ground-based observations

Surface solar radiation data

BSRN The Baseline Surface Radiation Network (BSRN) is a project of the World Climate Research Program (WCRP), which aims at detecting important changes in the Earth’s radiation fields [Ohmura et al., 1998; Wild et al., 2005] and providing reference data for the assessment of model and satellite-derived SSR. The BSRN provides high-quality surface radiation measurements at around 50 sites worldwide, some of them dating back to the early 1990’s. At these selected sites, covering a latitude range from 80°N to 90°S, SSR is measured with well-calibrated instruments of high accuracy producing 1-min averages from 1-s sampling.
The computation of monthly mean values follows the recommended approach as described in Roesch et al. [2011]. For BSRN-type pyranometer measurements, as used in this study, the GEWEX Radiative Flux Assessment (RFA) [Dutton and Long, 2012] reports operational uncertainties (95% inclusion ranges) of on average $\pm 8 \text{ W m}^{-2}$ for monthly mean and $\pm 6 \text{ W m}^{-2}$ for yearly mean values based on the comparison of redundant measurements at a number of NOAA radiation field sites.

There are 7 BSRN sites with sufficient data during the study period (2000–2010) located within the European domain as defined above: Cabauw, Camborne, Carpentras, Lerwick, Lindenber, Payerre, and Toravere. The data is distributed via the World Radiation Monitoring Center (WRMC) hosted by the Alfred Wegener Institute (AWI) in Bremerhaven, Germany (http://www.bsrn.awi.de/).

**GEBA** The Global Energy Balance Archive (GEBA), maintained at the Institute for Atmospheric and Climate Science at ETH Zurich, is a database for worldwide measurements of energy fluxes at the Earth’s surface [Gilgen and Ohmura, 1999] and is continuously updated with flux data mainly from the World Radiation Data Centre (WRDC) of the Main Geophysical Observatory in St. Petersburg. It contains more than 2’000 stations with more than 450’000 monthly mean values of various surface energy balance components, mainly downwelling SSR. Many records date back to the 1960s. Compared to the BSRN, the GEBA has the advantage of a much higher density of stations, however at the expense of the quality of the measurements, which often cannot compete with the BSRN.

Pyranometer measurements are known to have instantaneous accuracy limitations of 3–5% [Michalsky et al., 1999; Wild et al., 2013]. Their accuracy in the field has been estimated by Gilgen et al. [1998], who compared long-term SSR pyranometer measurements of five pairs of stations stored in the GEBA. While the absolute accuracy is unknown, the relative random measurement error is 5% of the monthly mean and 2% of the yearly mean values.

We use SSR timeseries from sites within our European domain (see above) that are found to be homogeneous during the study period. To assess the temporal homogeneity of the GEBA records, we follow the approach as described in Hakuba et al. [2013a], in which four different absolute homogeneity tests are applied to each series. In brief, a timeseries is considered inhomogeneous if at least three out of the four tests indicate a sudden shift in the mean or change in variance. Before applying the homogeneity tests, we removed monthly values that were flagged to be erroneous by the quality control as implemented in the GEBA [Gilgen and Ohmura, 1999]. We find 155 temporally homogeneous (at 99% significance level) GEBA records with monthly data covering at least 6 years within the period 2000–2010, less than 30% data gaps, and at least one complete annual cycle.

**Representativeness of point measurements**

In the present work, we combine the above SSR point measurements with collocated 1° grid cell values of TOAnet from satellites. To quantify the uncertainty in ASRSurf and ASRAtm due to this spatial mismatch, it is important to know how representative an SSR point measurement is for its larger surrounding, or specifically for the 1° satellite resolution used here. Hakuba et al. [2013b] have quantified the representativeness of measurement sites for their collocated CERES 1° grid cells using high-resolution (0.03°) SSR data from the Satellite Application Facility on climate monitoring (CM SAF, see Section 5.2.2). They define the representativeness of a measurement site by means of the spatial sampling error (SSE), which compares the CM SAF 0.03° pixel value collocated with the surface site location, to the 1° area mean computed...
from the CM SAF SSR. The absolute mean SSE at 134 surface sites (GEBA) determined in this way is around 2% (relative to the site value) on a climatological annual mean (2001-2005) basis and 4% for monthly means. Repeating the analysis in Hakuba et al. [2013b] for the period 2000–2010 yields similar numbers. By correcting the SSR records for their site-specific SSE (the deviation of the point value from the average over its surrounding or CERES 1° grid cell), the uncertainty due to the spatial mismatch can be reduced. For this purpose, we compute climatological monthly mean SSE (2000–2010) for each of the SSR measurement sites used in this study following Hakuba et al. [2013b] and remove those from the original SSR series. These SSE-corrected SSR series are then used to compute ASRsurf and ASRatm (Section 5.3).

5.2.2 Satellite observations

TOA fluxes

Solar radiation absorbed by the climate system (net solar radiation at TOA, TOAnet) is derived from satellite-based measurements of the total solar irradiance at TOA (TOAin) and the reflected shortwave flux (TOAup). The solar constant, based on the most recently launched SORCE Total Irradiance Monitor (TIM), is determined at 1360.8 ±0.5 Wm⁻² (annual mean), with reported uncertainties as low as 0.035% [Kopp et al., 2005; Kopp and Lean, 2011], which yields a global mean TOAin value of approximately 340 Wm⁻².

TOAup stems from the CERES mission that measures filtered radiances in the solar part of the spectrum (0.3 to 5μm) [Wielicki et al., 1996]. The solar TOA fluxes above the surface observation sites used in the present study are based on the energy balanced and filled (EBAF) dataset for the period 2000-present version EBAF 2.7 [Loeb et al., 2012]. The shortwave and longwave TOA fluxes in this dataset are adjusted within their range of uncertainty to be consistent with independent estimates of the global heating rate inferred from in-situ ocean observations and model simulations [Loeb et al., 2009, 2012]. The global mean TOAup of this dataset during the period 2000–2010 is 100 Wm⁻² with a stated uncertainty in absolute calibration of 2% (2σ), corresponding to 2 Wm⁻² [Loeb et al., 2009]. The CERES EBAF product provides monthly averages of TOA fluxes at a spatial resolution of 1° under both clear- and all-sky conditions and sets our grid for the entire study. All other quantities are treated with respect to this grid.

Surface albedo

Surface albedo is defined as the ratio of upwelling to downwelling solar radiation at the surface. Although a quite dense network of SSR observation sites exists, the upwelling fluxes are rarely measured and archived [Ohmura and Gilgen, 1993]. From all observational sites considered here, only the BSRN sites Payerne (Switzerland) and Toravere (Estonia) provide both, the downwelling and upwelling solar fluxes. Since in-situ observations of surface albedo are typically measured over short grass on the lawns of the meteorological sites, they cannot be considered representative for the surface albedo of their larger surrounding or collocated 1° grid cell as needed here. They are, however, of use for the validation of high-resolution satellite-derived albedo datasets, as discussed further below. The question of spatial representativeness has been addressed for SSR in Section 5.2.1, but is even more crucial for the reflectivity of heterogeneous land surfaces. To obtain a reliable area mean (1°) based on direct observations, multiple ground measurements would be needed to cover at least the major surface types [e.g., Li et al., 2002], which is beyond feasibility in the present study. The albedo needed in our approach (variable A in equation 5.2), thus, cannot be inferred from surface measurements
alone. Only satellite products can provide the spatial coverage needed, which brings along the question of the quality of satellite-based surface albedo datasets.

To date, the presumably most recognized and best validated satellite-derived dataset of surface albedo is provided by the Moderate Resolution Imaging Spectroradiometer (MODIS) [Schaaf et al., 2002] on the Terra and Aqua platforms. Here, we make use of the MCD43C3 Climate Modeling Grid (CMG) Albedo Product at the shortwave band (0.3-5 µm) available for 23 sixteen-day periods per year, which provides both the intrinsic white-sky (bihemispherical, [Lucht et al., 2000]) and black-sky (directional hemispherical, at mean solar local noon) albedos. The global surface albedo product is of 0.05° spatial resolution, covers the period 2000-present, and provides quality information through quality assurance flags. On their homepage (http://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD43), the NASA MODIS land team states a general accuracy of 5% or better for high quality MODIS operational albedo at 500m spatial resolution. Even albedo values with low quality flags have been found to be within 10% of the in-situ data studied thus far.

Numerous studies have validated the MODIS land surface albedo against in-situ measurements and yielded an absolute accuracy (average absolute biases) of 0.02-0.05, at least during snow-free periods [e.g., Liang et al., 2002; Jin et al., 2003; Roesch et al., 2004; Salomon et al., 2006; Liu et al., 2009; Rutan et al., 2009; Roman et al., 2013]. In many cases, the biases tend to be negative, and their magnitude increases in the presence of snow and/or when the Sun is low (solar zenith angle > 70°) [e.g., Roesch et al., 2004; Salomon et al., 2006; Liu et al., 2009; Cescatti et al., 2012; Rutan et al., 2009]. Two main approaches have been used to compare medium to low resolution satellite data with in-situ albedometer measurements. The first approach is to acquire in-situ measurements on top of tall towers to increase the footprint of the albedometer within the satellite pixel. The second approach selects in-situ measurement sites based on their representativeness for the surrounding landscape at medium resolution using high-resolution satellite data and spatial variogram analysis [Roman et al., 2009, 2013; Cescatti et al., 2012].

In order to compare or combine the MODIS albedo with other data of coarser spatial resolution (such as the CERES EBAF data), the data are aggregated onto the respective grid. The effect of this spatial averaging on our estimates of ASRsurf and ASRatm is small, as we will show in Section 5.4.3.

Another surface albedo dataset used in the present study, primarily for comparison purposes, is inferred from the CERES EBAF surface product [Kato et al., 2013] version 2.7 by taking the ratio of upwelling to downwelling SSR given in there. The CERES mission estimates surface irradiance through radiative transfer calculations using satellite-retrieved surface, cloud, and aerosol properties as input [Rutan et al., 2009; Doelling et al., 2013; Kato et al., 2011, 2013]. The monthly mean data at 1° spatial resolution cover the period 2000-present.

Rutan et al. [2009] compared the surface albedo derived from the Clouds and Radiation Swath product (CERES CRS, footprint level) to other satellite-based products and a number of in-situ measurements. With respect to ground-based observations they found for both, CERES CRS and MODIS, negative biases between -0.02 to -0.05 (10%-25%), which is in line with the studies mentioned above. Moreover, they found very good agreement between the CERES CRS and MODIS-derived surface albedos with a monthly mean difference of -0.004 (-2.4%). As we will show in Section 5.3.1, the CERES EBAF and MODIS-derived surface albedos are in good agreement as well, at least within the spatial and temporal domain considered here.

In view of the above considerations, we adopt an uncertainty of up to ±0.05 for both, the CERES EBAF and the MODIS-derived surface albedos (Section 5.4). In our analysis (Section 5.3), we make use of both surface albedo products. Together with SSR from the BSRN, we
compute ASRsurf and ASRatm twice (Section 5.3.2). Considering the denser network obtained from the GEBA, the analysis is primarily based on the MODIS product. However, in cases where a grid cell average based on MODIS cannot be computed due to missing values, the CERES EBAF albedo is used instead (Section 5.3.3).

**Satellite-derived surface solar radiation**

We do not use the satellite-based SSR described here to compute ASRatm and ASRsurf, but only to quantify the spatial representativeness of the SSR observation sites [Hakuba et al., 2013b] and the non-linear dependence between spatially averaged surface albedo and SSR (Section 5.4.3). For these purposes, we have chosen the continuous high-resolution (0.03°) SSR data record derived from the Meteosat first generation satellites (MFG) by the Satellite Application Facility on Climate Monitoring (CM SAF, www.cmsaf.eu, [Schmetz et al., 2002; Schulz et al., 2009]). The SSR data are based on the visible channel (0.45 - 1 μm) of the MVIRI (METEOSAT Visible and Infrared Imager) instruments on-board the MFG satellites. The processing employed a climate version of the Heliosat algorithm [Beyer et al., 1996; Cano et al., 1986], which includes a self-calibration method and an improved algorithm for the determination of the clear-sky reflectivity [Posselt et al., 2012]. For more details about the dataset, we refer to Mueller et al. [2011] and Posselt et al. [2011a, 2012]. The mean absolute difference of the monthly mean CM SAF SSR as compared to ground-based observations from the BSRN and the GEBA is around 8 Wm⁻² [Posselt et al., 2011a, 2011b; Sanchez-Lorenzo et al., 2013]. The CMSAF SSR data are available as monthly, daily, and hourly means at 0.03° spatial resolution covering the period 1983-2005.

### 5.3 Results

#### 5.3.1 Surface albedo

The surface albedo is an essential but critical parameter in the present study. As detailed in Section 5.2.2, we need to rely on validated satellite-based datasets and have chosen the surface albedos derived from MODIS and CERES EBAF. In the following, we compare their annual mean values (2000–2010, based on coinciding monthly means) at 115 grid cells over Europe land as collocated to the GEBA sites considered here (see Section 5.3.3). The 0.05° MODIS white-sky albedo is therefore aggregated onto the 1° CERES grid. Figure 5.2 depicts a scatter plot of the MODIS (x axis) and CERES (y axis) surface albedo values and indicates the ±0.02 and ±0.05 deviations as well as the 1:1 line. Overall, the two largely independent products agree to within their estimated uncertainty (see Section 5.2.2) of ±0.05 in absolute units. The mean difference (MODIS minus CERES EBAF) of -0.008 absolute or 5% relative to the MODIS mean (0.152) originates from a slightly “brighter” CERES surface albedo during the winter months by 0.016. In summer, CERES is lower than MODIS by around 0.005. Mean absolute deviation and root-mean-squared-error (RMSE) are both around 0.02. 90% of all values agree to within 10% accuracy, 80% within 5%, 70% within 2%.

Rutan et al. [2009] found very good agreement between MODIS and CERES-retrieved surface albedos (snow-free) at 25 selected sites, with CERES being slightly “darker” than MODIS by 0.004 (2.4%), which is contradicting the above findings. However, this is not necessarily surprising, since they essentially assessed a different CERES product (CERES CRS, Section 5.2.2), compared the albedos under snow-free conditions only, and used different locations.
From the above, we conclude that we can either work with the MODIS or CERES-derived surface albedo, as there is no significant systematic bias between the two. Nevertheless, we take into account an uncertainty of at most ±0.05 as compared to in-situ observations (see Section 5.2.2).

### 5.3.2 Absorption at European BSRN sites

Following equation 5.1 and 5.2, we combine the monthly mean SSR records from 7 BSRN sites as listed in Table 5.1 with their collocated records of surface albedo (MODIS aggregated onto 1° grid) and TOAnet (CERES EBAF). Table 5.1 presents the annual mean SSR, ASRsurf, ASRatm, TOAnet, and TOAin estimates at the individual sites and as sample average over all sites. The fractional absorption estimates (fraction of incoming irradiance at TOA) are given in brackets. Working with these normalized values eliminates to a large degree the strong latitudinal dependence of absolute radiation values. The sample averages of absolute (fractional) ASRsurf and ASRatm are 112.6 Wm$^{-2}$ (41.2%) and 59.1 Wm$^{-2}$ (21.6%).

As pointed out in Section 5.2.1, the spatial representativeness of the SSR measurement sites for their collocated 1° grid cells of the satellite products is a source of uncertainty in the approach presented here. Improving the spatial representativeness of the BSRN sites according to Hakuba et al. [2013b] by eliminating the monthly mean spatial sampling error (SSE) caused by the subgrid scale variability of SSR (see Section 5.2.1) results in sample-averaged absolute (fractional) ASRsurf and ASRatm of 110 Wm$^{-2}$ (40.3%) and 61.7 Wm$^{-2}$ (22.6%). In Table 5.1, corresponding values are indicated by a prime, e.g., ASRsurf’. The partitioning between surface and atmospheric absorption is shifted by 1% towards an increase in ASRatm when SSE corrections are applied.

The site Carpentras absorbs by far the most solar radiation at the surface. It not only receives more SSR because of its Southerly and comparably sunny location, also the annual mean surface albedo is lower in this area due to reduced or non-existent snow cover as compared to
Table 5.1: Annual mean (2000–2010) estimates of SSR, ASRsurf, ASRatm, TOAnet, TOAin at 7 European BSRN sites (Wm$^{-2}$) using MODIS surface albedo. In brackets the estimates are given as fraction of TOAin (%). SSR’, ASRsurf’, ASRatm’, ASRatm'/ASRsurf' are based on SSE-corrected SSR records (section 5.2.1). See text for details.

<table>
<thead>
<tr>
<th>Station</th>
<th>SSR</th>
<th>SSR’</th>
<th>ASRsurf</th>
<th>ASRsurf’</th>
<th>ASRatm</th>
<th>ASRatm’</th>
<th>TOAnet</th>
<th>TOAin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cabauw (NE)</td>
<td>123.1</td>
<td>123.8</td>
<td>105.3</td>
<td>105.83</td>
<td>63</td>
<td>62.5</td>
<td>168.2</td>
<td>0.59</td>
</tr>
<tr>
<td>Camborne (GB)</td>
<td>125.6</td>
<td>127.4</td>
<td>121.2</td>
<td>122.8</td>
<td>62.4</td>
<td>60.8</td>
<td>183.2</td>
<td>0.50</td>
</tr>
<tr>
<td>Carpentras (FR)</td>
<td>180.4</td>
<td>164.9</td>
<td>154.0</td>
<td>140.8</td>
<td>56.3</td>
<td>57.0</td>
<td>210.3</td>
<td>0.49</td>
</tr>
<tr>
<td>Lerwick (GB)</td>
<td>90.8</td>
<td>86.2</td>
<td>85.9</td>
<td>82.3</td>
<td>56.5</td>
<td>57.8</td>
<td>142.7</td>
<td>0.73</td>
</tr>
<tr>
<td>Lindenberg (DE)</td>
<td>125.0</td>
<td>125.3</td>
<td>106.5</td>
<td>106.8</td>
<td>61.3</td>
<td>60.1</td>
<td>167.6</td>
<td>0.57</td>
</tr>
<tr>
<td>Payerne (CH)</td>
<td>144.7</td>
<td>141.1</td>
<td>122.6</td>
<td>119.5</td>
<td>57.0</td>
<td>57.8</td>
<td>179.2</td>
<td>0.5</td>
</tr>
<tr>
<td>Toravere (EE)</td>
<td>111.2</td>
<td>110.4</td>
<td>93.0</td>
<td>92.3</td>
<td>57.0</td>
<td>57.8</td>
<td>150.3</td>
<td>0.63</td>
</tr>
<tr>
<td>Station avg.</td>
<td>128.7</td>
<td>125.7</td>
<td>112.6</td>
<td>110.0</td>
<td>59.1</td>
<td>61.7</td>
<td>171.6</td>
<td>0.56</td>
</tr>
</tbody>
</table>

the more Northerly located BSRN sites. Nevertheless, the fractional ASRatm is in accordance with the station average.

Figure 5.3 depicts the annual cycles of the fractional TOAnet, ASRsurf, and ASRatm (solid lines) and their absolute counterparts (dashed lines) based on the SSE-corrected SSR records at the 7 BSRN sites. The shading illustrates the inter-annual variability in terms of $\pm 1\sigma$ of the fractional values. All sites show the typical annual cycles with most radiation being absorbed in the summer months, especially in absolute units. The only notable exception is the fractional ASRatm which seems rather constant and free of any obvious annual cycle. If any, it shows an opposing signal as compared to fractional ASRsurf, e.g., at Cabauw or Payerne. Not only throughout the seasons, but also throughout the years (shading of $\pm 1\sigma$), fractional ASRatm is more robust than the other quantities.

Another source of uncertainty in our computations of ASRsurf and ASRatm, besides the spatial representativeness of the SSR point observations, is the choice of an adequate surface albedo product. We therefore repeat the preceding analysis using the independent surface albedo derived from the CERES EBAF surface solar fluxes (see Section 5.2.2). Comparing ASRsurf and ASRatm based on the different products, we select only those months that are covered by both products, MODIS being aggregated onto the CERES standard grid of 1° resolution. We calculate the mean annual cycles of ASRsurf and ASRatm based on the different albedo products to assess also the seasonal dependence of the biases (not shown).

We find station-averaged annual mean surface albedos of 0.15 (CERES) and 0.13 (MODIS). The higher CERES albedo results in, on average, 2 Wm$^{-2}$ less (more) ASRsurf (ASRatm). The station-averaged fractional ASRatm is 22.7% using the MODIS albedo and 23.4% using the CERES product. Especially Toravere, Lindenberg, and Lerwick show very good agreement with biases in ASRatm below or around 0.5 Wm$^{-2}$. At Camborne, Cabauw, Carpentras, and Payerne, differences are between 2–6 Wm$^{-2}$.

Further sources of uncertainty in the ASRsurf and ASRatm estimates retrieved here are discussed in Section 5.4.

5.3.3 Absorption at European GEBA sites

Compared to the BSRN, many more European sites are available from the GEBA. Thus here, the computation of ASRsurf and ASRatm is built upon 137 CERES grid cells as collocated with 155 GEBA sites. 14 grid cells are collocated with multiple (max. 5) GEBA sites; their SSR records are averaged prior to the combination with surface albedo to obtain ASRsurf. Four
Figure 5.3: Mean annual cycles (2000–2010) of absolute (dashed lines) and fractional (with respect to TOAin, solid lines) TOA\textsubscript{net} (red), ASR\textsubscript{surf} (green), and ASR\textsubscript{atm} (blue) at 7 BSRN sites as listed in table 5.1. Surface albedo stems from MODIS. SSR is SSE-corrected. The shading indicates the $\pm 1\sigma$ scatter across years.

GEBA sites lie on the border of two grid cells. In these cases, both grid cells are included in the present analysis.

In the following, we use both the MODIS and the CERES surface albedo to compute ASR\textsubscript{surf} and ASR\textsubscript{atm} in combination with SSR from the GEBA. MODIS is our first choice, but in grid cells for which we cannot compute a MODIS-based area average due to missing values, we use the CERES albedo instead. Since MODIS provides a land surface albedo product, missing values particularly in coastal $1^\circ$ grid cells are inevitable. Furthermore, we use only values that are flagged as high quality, reducing the amount of available pixels even more. An area average ($1^\circ$ grid cell) of MODIS surface albedo is only computed if less than 40% of the comprised pixels are missing. 11 grid cells fail in this respect and the CERES-derived surface albedo is used instead.

From the 137 grid cells, referred to as “all”, we distinguish the subset “land”: 115 CERES grid cells over land, i.e., at least 50% land according to the CERES FSW Water/Land Percentage map (http://www-surf.larc.nasa.gov/surf/pages/water.html). Furthermore, we calculate ASR\textsubscript{surf} once with and once without SSE-corrected SSR records (“SSE-corr”, see Sections 5.2.1 and 5.3.2). In the case of multiple sites per CERES grid cell, the SSE refers to the multiple sites’ average SSR record.

The maps in Figure 5.4 depict all 137 CERES grid cells (in color) as collocated to the 155 GEBA sites (red dots). Shown are the annual mean (2000–2010) ASR\textsubscript{surf} (top, left) and
Figure 5.4: Annual mean absolute (Wm$^{-2}$, top panels) and fractional (%) ASRsurf (left) and ASRatm (right) based on the combination of 137 CERES grid cells with 155 collocated GEBA sites (red dots). Surface albedo stems from MODIS. SSR is SSE-corrected.

The annual mean ASRatm (top, right) in Wm$^{-2}$, as well as the fractional ASRsurf (bottom, left) and fractional ASRatm (bottom, right) in % of TOAin. The spatial pattern of ASRsurf is dominated by a distinct North-South gradient ranging from around 80 Wm$^{-2}$ to 180 Wm$^{-2}$. The spatial distribution of (fractional) ASRatm is much more homogeneous, yet, it appears that elevated topography, such as the Alps or the Spanish plateau, where the overlying air-mass is reduced as compared to flat terrain, decreases the (fractional) ASRatm.

Table 5.2 summarizes the “all” and “land” sample averages of the variables studied here, as well as their SSE-corrected twins. The notion that ASRsurf is lower over land is physically consistent, due to the different surface albedos of land and sea. The SSE-correction leads to only small changes in the (fractional) absorption estimates.

Figure 5.5 shows the corresponding (“all”, SSE-corrected) average annual cycles of the absolute (top) and fractional (bottom) TOAnet, ASRsurf, and ASRatm in Wm$^{-2}$ and percent, respectively. Similar as with the BSRN sites (Section 5.3.2.), the fractional components show weaker annual cycles than their absolute counterparts. Again, the fractional ASRatm appears rather constant with no obvious seasonal variations and a mean value of around 23%.

In the simple dataset average just performed, the spatial distribution of the GEBA sites and their collocated grid cells may result in an unequal representation of different latitudes and regions. We take this to a first order into account and compute zonal averages from the absorption estimates prior to the computation of the European mean. The associated latitudinal weighting...
Table 5.2: Annual mean (2000–2010) estimates of SSR, ASRsurf, ASRatm, \( \frac{\text{ASRatm}}{\text{ASRsurf}} \), TOAnet, and TOAin (Wm\(^{-2}\)) averaged over 6 different GEBA-based subsets. "all": 137 grid cell estimates, "land": 115 grid cell estimates over land only, "SSE-corr": SSR records are SSE-corrected (section 5.2.1), "latw.": subset average is based on latitudinally weighted (zonally averaged) grid cell estimates. MODIS surface albedo is used in the majority of estimates. If MODIS is missing, CERES EBAF is used instead. In brackets the estimates are given as fraction of TOAin (%).

<table>
<thead>
<tr>
<th>GEBAs-based subsets</th>
<th>SSR</th>
<th>ASRsurf</th>
<th>ASRatm</th>
<th>TOAnet</th>
<th>( \frac{\text{ASRatm}}{\text{ASRsurf}} )</th>
<th>TOAin</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>141.1</td>
<td>122.0 (42.3)</td>
<td>66.5 (23.0)</td>
<td>188.5</td>
<td>0.55</td>
<td>288.9</td>
</tr>
<tr>
<td>all SSE-corr</td>
<td>140.7</td>
<td>121.7(42.1)</td>
<td>66.8 (23.1)</td>
<td>188.5</td>
<td>0.55</td>
<td>288.9</td>
</tr>
<tr>
<td>all SSE-corr latw.</td>
<td>140.8</td>
<td>122.5 (43.1)</td>
<td>65.1 (22.9)</td>
<td>187.7</td>
<td>0.53</td>
<td>284.3</td>
</tr>
<tr>
<td>land</td>
<td>140.7</td>
<td>119.6 (44.1)</td>
<td>66.1 (22.9)</td>
<td>185.7</td>
<td>0.55</td>
<td>288.7</td>
</tr>
<tr>
<td>land SSE-corr</td>
<td>140.1</td>
<td>119.0 (41.2)</td>
<td>66.7 (23.1)</td>
<td>185.7</td>
<td>0.56</td>
<td>288.7</td>
</tr>
<tr>
<td>land SSE-corr latw.</td>
<td>137.9</td>
<td>117.3 (41.6)</td>
<td>65.0 (23.0)</td>
<td>182.3</td>
<td>0.55</td>
<td>282.1</td>
</tr>
</tbody>
</table>

yields European “land” mean values of absolute (fractional) ASRsurf: 117.3 Wm\(^{-2}\) (41.6%) and ASRatm: 65.0 Wm\(^{-2}\) (23.0%). Figure 5.6 illustrates the corresponding zonal averages of annual mean TOAnet (red), ASRsurf (green), and ASRatm (blue), both in absolute units (left panel) and expressed as fraction of TOAin (right panel). As can be seen, (fractional) TOAnet and (fractional) ASRsurf grow in concert with each other from North to South, suggesting that local, latitude dependent effects are superimposed on the astronomically induced North-South gradient in TOAin. Potential candidates are surface albedo and cloud effects, driven by the different climate regimes in Southern and Northern Europe. Differing topographic height may at least partially explain the scatter at fixed latitudes, e.g., the Pyrenees (around 43° N) and the Alps (around 46° N). Also a role play changes in cloud cover associated with the shift from a more maritime climate in the West to a more continental climate in the East. The fractional ASRatm stays comparatively constant at around 23%, without any clear latitudinal dependence.

5.3.4 Regional means – spatial coverage

From Figure 5.4 it is apparent that the spatial coverage provided by the GEBA sites is substantial, yet far from complete. The associated question of the robustness of our European mean estimates has already been addressed in Section 5.3.3. Here, we take this up again.

To increase the number of available grid cells beyond the 115 grid cells collocated with at least one GEBA site over Europe land, we use the geostatistical mapping method Ordinary Kriging (OK) in combination with grid cell based, multiplicative correction factors to remove interpolation biases as described in Journé and Bertrand [2010, 2011]; Journé et al. [2012]. However, we stress that our goal is not to provide a gridded, gap-free GEBA-based product for Europe, but only to augment the spatial coverage visible in Figure 5.2 and to assess its influence on the estimated European means.

To determine the grid cell based, multiplicative correction factors, we start from satellite-derived ASRsurf over Europe land (-9° to 31° East, 36° to 64° North) estimated from the CERES EBAF surface dataset version 2.7. We apply the OK method using only those 115 grid cells of the satellite-derived ASRsurf map that are collocated with our GEBA sites and compare the resulting map with the same satellite-derived ASRsurf we started with. Obviously, the OK produces best results in regions that are sufficiently covered by observational grid cells.
to interpolate with. Interpolation biases larger than ±10% are found in Norway and Greece due to the sparse site density there. Following Journée and Bertrand [2010], we derive from these interpolation biases multiplicative correction factors for each grid cell. If applied to the interpolated data, the original CERES EBAF ASRsurf is recovered.

In a second step, we apply OK again, but this time to our GEBA/MODIS-based ASRsurf dataset, consisting of the 115 grid cell estimates over Europe land. We use our CERES-based multiplicative factors to correct the biases of the OK interpolation and thereby tacitly assume that the error structure of pure satellite-based kriging and GEBA-based kriging is similar. This approach yields an area-weighted regional mean ASRsurf of 117.8 Wm$^{-2}$ (40.7%). Combining this map with TOAnet from CERES EBAF attains a regional mean ASRatm estimate of 67.1 Wm$^{-2}$ (23.5%). For comparison, if no bias correction is applied, we obtain area-weighted regional mean ASRsurf of 118.1 Wm$^{-2}$ (40.9%) and ASRatm of 66.8 Wm$^{-2}$ (23.3%). For the European mean, the bias correction is not too crucial and both approaches yield results in good agreement with the estimates in Table 5.2.

Figure 5.7 shows the spatially interpolated maps (OK, interpolation bias removed) of the GEBA-based ASRsurf (top left) and ASRatm (top right), the residual of combining ASRsurf with CERES-derived TOAnet. The grid cell values used for OK are indicated by red dots. The fractional ASRsurf and ASRatm are shown in the lower panels. As expected from Figure 5.4, the North-South gradient is evident in ASRsurf, whereas the pattern of ASRatm seems to be more dominated by altitude effects.

From the spatially complete datasets in Figure 5.7, we compute regional means of four subdomains, which are covered by at least 9 GEBA-based individual column estimates, namely the PRUDENCE regions [e.g., Christensen and Christensen, 2007; Bellprat et al., 2012]: Mid-Europe (ME, 22 individual column estimates), France (FR, 9), Alps (AL, 15), and Iberian Peninsula (IP, 21). These regional means are computed once without and once with the interpolation biases removed (OK GEBA and OK GEBA bias-corr in Table 5.3). Thirdly, we compute the regional means by averaging the individual GEBA-based absorption estimates (latitudinally weighted) derived in Section 5.3.3. Within a region, the area means based on these three different methods are in remarkable agreement, with differences in ASRsurf and
ASRatm of at most 2 Wm$^{-2}$ (see Table 5.3). The spread between the regions is on the order of 50 Wm$^{-2}$ in ASRsurf, decreasing down to 10 Wm$^{-2}$ in ASRatm. Differences in fractional ASRsurf and ASRatm are up to 10% and 3% respectively, indicating superior spatial robustness of fractional ASRatm as compared to ASRsurf. Nevertheless, the pinpoint value of 23% is hardly met by any of the regions. As both the Alps and Iberian peninsula are characterized by high terrain, it is no surprise that fractional ASRatm is reduced, whereas the low-altitude regions Mid-Europe and France show an opposite signal.

### 5.3.5 Satellite-based European mean Absorption

All estimates of ASRsurf and ASRatm presented so far made use of surface observations (BSRN and GEBA). Here, we compare these results with pure satellite-based regional means over Europe land (2000–2010). The CERES EBAF dataset provides both, the shortwave fluxes at TOA and at the surface, thus allows to assess the solely satellite-based partitioning of solar absorption. Computing area weighted Europe land means between $-9^\circ$ to $31^\circ$ East and $36^\circ$ to $64^\circ$ North, we find fractional ASRatm of 23.4% (absolute: 67.4 Wm$^{-2}$) and fractional ASRsurf of 40.6% (117.3 Wm$^{-2}$), which is already in good agreement with the GEBA/MODIS-based estimates (see Table 5.2). A more legitimate comparison is achieved by just picking out the 115 grid cells over Europe land as collocated to the GEBA sites (annual means based on coinciding monthly means). CERES EBAF slightly underestimates (overestimates) the sample mean ASRsurf (ASRatm) by 1.2 Wm$^{-2}$ and the mean absolute deviation is 4.3 Wm$^{-2}$. The latitude-weighted averaging yields European mean ASRsurf of 116.4 Wm$^{-2}$ (41.3%) and ASRatm of 65.9 Wm$^{-2}$ (23.4%), again in good agreement with the GEBA/MODIS-based estimates (Table 5.2). Spatially, in terms of zonal averages (not shown), CERES EBAF is in agreement with the preceding analysis as well. Notable is, however, the reduced spread at fixed latitudes for ASRatm that also shows in a reduced $\sigma$ (spatial scatter) from 8 Wm$^{-2}$ down to 6 Wm$^{-2}$, again indicating a homogeneous spatial distribution. From this analysis we may draw two conclusions. On the one hand, the CERES EBAF product is capable of representing the partitioning of solar absorption realistically as compared to our previously derived dataset. On the other hand, the results support the finding of a spatially robust fractional ASRatm of around 23%.

![Figure 5.6: Zonal averages of absolute (left) and fractional (right) annual mean TOAnet (red), ASRsurf (green), and ASRatm (blue). SSR records are SSE-corrected. The dots represent the individual estimates and thus the longitudinal scatter.](image-url)
Table 5.3: Regional means of ASRsurf and ASRatm in Europe (EU) and 4 PRUDENCE regions: Mid-
Europe (ME, 22 GEBA-based absorption estimates), France (FR, 9), Alps (AL, 15), and Iberian Penin-
sula (IP, 21). Regional means are based on spatially interpolated (ordinary kriging, OK) GEBA-based
ASRsurf once without and once with interpolation biases removed (bias-corr), and from latitudinally
weighted (latw.) individual grid cell estimates (GEBA-based) over Europe land. Absolute values of
ASRsurf and ASRatm are given in Wm$^{-2}$. In brackets the estimates are given as fraction of TOAin (%).

<table>
<thead>
<tr>
<th></th>
<th>OK GEBA</th>
<th>OK GEBA bias-corr</th>
<th>GEBA latw.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASRsurf</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EU</td>
<td>118.1 (40.9)</td>
<td>117.8 (40.7)</td>
<td>117.3 (41.6)</td>
</tr>
<tr>
<td>ME</td>
<td>105.5 (37.7)</td>
<td>104.6 (37.4)</td>
<td>105.4 (37.8)</td>
</tr>
<tr>
<td>FR</td>
<td>116.9 (39.3)</td>
<td>118.0 (39.7)</td>
<td>115.9 (39.1)</td>
</tr>
<tr>
<td>AL</td>
<td>129.9 (43.1)</td>
<td>130.2 (43.2)</td>
<td>130.2 (43.2)</td>
</tr>
<tr>
<td>IP</td>
<td>155.5 (47.9)</td>
<td>155.0 (47.7)</td>
<td>156.6 (48.1)</td>
</tr>
<tr>
<td>ASRatm</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EU</td>
<td>66.8 (23.3)</td>
<td>67.1 (23.5)</td>
<td>65.0 (23.0)</td>
</tr>
<tr>
<td>ME</td>
<td>65.0 (23.3)</td>
<td>65.9 (23.6)</td>
<td>66.2 (23.7)</td>
</tr>
<tr>
<td>FR</td>
<td>70.5 (23.8)</td>
<td>69.5 (23.4)</td>
<td>70.8 (23.9)</td>
</tr>
<tr>
<td>AL</td>
<td>62.1 (20.6)</td>
<td>61.8 (20.5)</td>
<td>60.8 (20.2)</td>
</tr>
<tr>
<td>IP</td>
<td>70.9 (21.9)</td>
<td>71.4 (22.0)</td>
<td>72.5 (22.2)</td>
</tr>
</tbody>
</table>

5.4 Uncertainties

Uncertainties in ASRsurf and ASRatm arise from the uncertainties of the employed datasets
(Section 5.4.1) as well as from their combination: the spatial representativeness of the SSR
point observations (Section 5.4.2), and the multiplication of SSR and surface albedo to get
ASRsurf in combination with spatial averaging (mean of the product versus product of the
means; Section 5.4.3). Besides these uncertainties, we also identified some systematic depen-
dencies (season, latitude, terrain height; Section 5.4.4). In the following, we quantify the above
uncertainties in ASRsurf and ASRatm and bundle them in two different ways: First, we com-
bine the above uncertainties through error propagation formulas [e.g., Bevington and Robinson,
2002] to obtain the uncertainty of an individual column estimate of ASRsurf and ASRatm (Sec-
tion 5.4.5) and secondly, we quantify the uncertainty of the dataset’s regional mean by means
of a t-test (Section 5.4.6).

5.4.1 Datasets’ measurement uncertainty

Each of the datasets used in the present study is associated with operational measurement
uncertainties that are documented in their respective data quality reports or related publications.
Here, we summarize the uncertainty ranges of the SSR, surface albedo, and TOAnet datasets.

Operational uncertainties of pyranometer (SSR) measurements (BSRN, GEBA) are re-
ported to be ±8 Wm$^{-2}$ for monthly means and ±6 Wm$^{-2}$ for annual means [Dutton and
Long, 2012], which is around 6% and 4% with respect to our best estimate of annual mean
SSR (see Table 5.2: 138 Wm$^{-2}$, “land SSE-corr latw.”). For the surface albedo products, we
adopt a conservative uncertainty (absolute accuracy as compared to in-situ measurements) of
±0.05 as discussed in Sections 5.2.2 and 5.3.1. This uncertainty translates into ±6 Wm$^{-2}$
with respect to our best estimate of ASRsurf (117 Wm$^{-2}$, “land SSE-corr latw.”) and is thus on
5.4 Uncertainties

Figure 5.7: Maps of annual mean ASRsurf (left) and ASRatm (right) based on spatial interpolation (ordinary kriging) of the GEBA/MODIS-based subset of 115 grid cells (1°) over European land (Wm\(^{-2}\)). Fractional ASRsurf and ASRatm (%) are shown below. Interpolation biases with respect to the solely satellite-based ASRsurf map (CERES EBAF) have been removed.

The same order as the uncertainty in SSR. The major sources of uncertainty in CERES-based TOAnet are from instrument calibration and are estimated at another 2% (2\(\sigma\)) [Loeb et al., 2009; Wong et al., 2012] or \(\pm 3.6\,\text{Wm}^{-2}\) with respect to our TOAnet annual mean estimate of 182 Wm\(^{-2}\).

5.4.2 Representativeness of point measurements

As pointed out by Hakuba et al. [2013a] the spatial representativeness of the SSR point measurements for their collocated CERES grid cells is another source of uncertainty for the absorption estimates computed here. The spatial sampling error (SSE) defined therein is around 4% for monthly mean and 2% for annual mean SSR at 134 GEBA sites with respect to their collocated CERES grid cells during the period 2001-2005. These results are in agreement with the SSE found for the GEBA sites and study period (2000–2010) used in the present work. However, in correcting for the SSE (Sections 5.3.1 and 5.3.2), we largely removed this source of uncertainty. For more details refer to Section 5.2.1.
**5.4.3 Mean of product, product of means**

As ASRsurf is essentially the product of SSR and surface albedo, it is not a priori clear what uncertainty is introduced by multiplying just the grid cell means of SSR and surface albedo – instead of doing the multiplication before the spatial averaging, i.e., multiplying first spatially highly resolved SSR and surface albedo and then taking the spatial mean. To obtain ASRsurf following equation 5.2, we combine the 0.03° satellite-retrieved SSR from CM SAF with the high-resolution MODIS white-sky surface albedo (30arc second, snow-free) aggregated onto the 0.03° grid. We then calculate the area mean of ASRsurf for each of the 563 CERES 1° grid cells over Europe land. For comparison, we first compute the grid cell means of SSR and surface albedo and then combine these means into values of ASRsurf. Figure 5.8 shows a scatter plot of the 563 ASRsurf mean values obtained by the “fine” (x axis, first multiply, then average) and “coarse” (y axis, first average, then multiply) combination of SSR and surface albedo for the climatological period (2001-2005). The Figure indicates very good agreement. To carve out the effect in question and to avoid spurious correlation, the North-South gradient in ASRsurf has been removed by subtracting the latitudinal means from Figure 5.6 and absolute values were taken (no negative anomalies). The mean bias and mean absolute bias between “fine” and “coarse” combination are 0.09 Wm$^{-2}$ and 0.13 Wm$^{-2}$, thus around 0.1% of ASRsurf. The maximum deviation is 4 Wm$^{-2}$, however 90% of all mean values show a deviation of less than 0.3 Wm$^{-2}$, 75% even less than 0.1 Wm$^{-2}$. These numbers show that taking the product of SSR and surface albedo grid cell means as opposed to computing the grid cell mean of their product, introduces only a small, comparatively negligible uncertainty.
5.4.4 Systematic dependencies

Besides the uncertainties discussed above, both, the individual column estimates and the regional means of ASRsrf and ASRatm are afflicted with systematic dependencies, as identified in Section 5.3. There is a clear seasonal dependence (higher values in summer than in winter), except for fractional ASRatm (e.g., Figure 5.5). Also apparent is a clear latitudinal dependence (higher values in the South), except again for fractional ASRatm (e.g., Figure 5.6). This latitudinal dependence is not only astronomically induced, but strongly depends on latitudinally varying cloud cover and surface albedo as well. Both these local effects are more relevant in Northern and Central Europe and dilute the gradient in ASRsrf at higher latitudes (e.g., Figure 5.6). Finally, Figure 5.4 and 5.7 suggest some terrain height dependence of ASRatm with lower values over elevated terrain due to a reduced total atmospheric column. These systematic dependencies should be kept in mind, especially the latitudinal dependence, as it makes the European mean estimate of ASRsrf strongly dependent on the North-South extent of the chosen domain.

5.4.5 Individual column uncertainty

Based on error propagation formulas using standard deviations [e.g., Bevington and Robinson, 2002], we combine the operational uncertainties of the employed datasets (Section 5.4.1) to estimate the uncertainties of the individual column computations of ASRsrf and ASRatm over Europe land (115 grid cells). Based on this analysis, the datasets’ operational uncertainties of 6 Wm$^{-2}$ in SSR, 0.05 in surface albedo, and 3.6 Wm$^{-2}$ in TOAnet, propagate into combined uncertainties of $\pm9.4$ Wm$^{-2}$ for an individual grid cell estimate of annual mean ASRsrf and $\pm10.1$ Wm$^{-2}$ uncertainty for an individual column estimate of annual mean ASRatm, corresponding to around $\pm3.5\%$ uncertainty in fractional ASRatm.

5.4.6 Sample mean uncertainty

The uncertainty of the sample’s mean (“land SSE-corr latw.” in Table 5.2) is evaluated based on Student’s t-test using the spatial scatter $\sigma$ across the 115 individual grid cell estimates and two-sided 95% confidence intervals (CI). Results are summarized in Table 5.4. We find the following sample mean uncertainties, the means themselves being our best estimates. ASRsrf: $117.3 \pm 4.4$ Wm$^{-2}$, ASRatm: $65.0 \pm 1.6$ Wm$^{-2}$, fractional ASRsrf: $41.6 \pm 1\%$, and fractional ASRatm: $23.0 \pm 0.4\%$. These uncertainty estimates neglect the uncertainties of the individual column computations (Section 5.4.5). Taking them into account by just adding them to the scatter $\sigma$ across sites (indicated by an asterisk in Table 5.4), yields the following sample mean uncertainties. ASRsrf: $117.3 \pm 6.1$ Wm$^{-2}$, ASRatm: $65.0 \pm 3.4$ Wm$^{-2}$, fractional ASRsrf: $41.6 \pm 1.6\%$, and fractional ASRatm: $23.0 \pm 1.1\%$.

The European means derived from spatially interpolated ASRsrf (Section 5.3.4) and from the solely satellite-based dataset (CERES EBAF) are well within these uncertainty ranges. Comparing the four PRUDENCE regions (Section 5.3.4), their regional means differ quite substantially from our European mean for both ASRsrf and ASRatm. This is to be expected due to the systematic dependencies given in Section 5.4.4. The PRUDENCE regional means lie, however, well within the $\pm1\sigma$ scatter around the mean ($\sigma$ in Table 5.4), the only exception being ASRsrf in the Iberian Peninsula.
Table 5.4: Uncertainty of sample mean of GEBA-based (fractional) ASRsurf and (fractional) ASRatm over Europe land (“land SSE-corr latw.,” see Table 5.2). Given are the latitudinally weighted sample means (annual, 2000–2010), their spatial scatter (σ), the uncertainty of the mean (1.96·σ/√N), and the 95% confidence intervals. N indicates the size of the sample, here 115 individual grid cell estimates are used. The asterisk indicates that the individual column uncertainty is added to the σ (see sections 5.4.5 and 5.4.6.).

<table>
<thead>
<tr>
<th></th>
<th>sample mean</th>
<th>σ</th>
<th>σ∗</th>
<th>1.96·σ/√N</th>
<th>1.96·σ/√N∗</th>
<th>95% CI∗</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASRsurf [Wm$^{-2}$]</td>
<td>117.3</td>
<td>24.1</td>
<td>33.5</td>
<td>4.4</td>
<td>6.1</td>
<td>[111.2, 123.4]</td>
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<tr>
<td>ASRatm [Wm$^{-2}$]</td>
<td>65.0</td>
<td>8.6</td>
<td>18.7</td>
<td>1.6</td>
<td>3.4</td>
<td>[61.6, 68.4]</td>
</tr>
<tr>
<td>frac. ASRsurf [%]</td>
<td>41.6</td>
<td>5.5</td>
<td>8.8</td>
<td>1.0</td>
<td>1.6</td>
<td>[40.0, 43.2]</td>
</tr>
<tr>
<td>frac. ASRatm [%]</td>
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<td>2.4</td>
<td>5.9</td>
<td>0.4</td>
<td>1.1</td>
<td>[21.9, 24.1]</td>
</tr>
</tbody>
</table>

5.5 Conclusions

By combining temporally homogeneous and spatially representative ground-based measurements of surface solar radiation (SSR) with collocated satellite-derived surface albedo and TOA net solar irradiance, we obtained a solid estimate of the solar absorption partitioning representative for Europe (-9° to 31° East and 36° to 64° North) during 2000–2010. Special emphasis was also given to the identification and quantification of associated uncertainties and systematic dependencies. Our best annual mean estimates of solar absorption at the surface (ASRsurf) and in the atmosphere (ASRatm) over Europe land are: 117.3 ±6.1 Wm$^{-2}$ (41.6 ±1.6% of TOA irradiance) and 65.0 ±3.4 Wm$^{-2}$ (23.0 ±1.1%). These European mean values were obtained by averaging the individual absorption estimates determined at 115 grid cells with prior latitudinal weighting. Both, simple averaging and spatial interpolation of the dataset, yield European mean values within the given range of uncertainty.

Overall, the approach of combining surface and satellite observations has proven suitable for the qualitative and quantitative determination of the European mean-state and spatial distribution of ASRsurf and ASRatm. The uncertainty of the individual absorption estimates is dominated by the operational uncertainties of the SSR, surface albedo, and TOA irradiance measurements. Other sources of uncertainty, like the multiplicative combination of spatially averaged SSR and surface albedo to obtain ASRsurf, as well as the spatial representativeness of the SSR point observations, are either shown to be negligibly small or can be corrected for.

Obviously, the absorption estimates vary with latitude and season. However, these systematic dependencies are more pronounced at the surface than in the atmosphere. Particularly the fractional ASRatm estimate of 23% is very robust in this respect, as it remains nearly constant in space and time. In the annual mean, its spatial scatter (±1σ) across all individual column estimates is 23% ±2.4%. Therefore, fractional ASRatm may serve as a straightforward first order measure for the validation of (regional) climate models.

A follow-up study will assess whether this partitioning holds also for other regions of the Earth or even on a global scale. Preliminary analyses look promising in this respect. Interestingly, the 23% of atmospheric solar absorption determined here happen to be in very good agreement with estimates of recent energy balance studies [Trenberth et al., 2009; Wild et al., 2013] that inferred atmospheric solar absorption using different approaches.

Focusing on Europe, the present study profited from the high density of SSR measurement sites. With regard to the spatial expansion of this study to larger scales, the availability of
ground-based observations is a critical aspect, since the coverage over some of the world’s continents, such as Africa or South America is rather poor. In these areas, the use of purely satellite-retrieved data might become necessary. Associated quality considerations then may profit from the quantitative insight gained here, particularly on sources of uncertainty, systematic dependencies, and the Europe-wide robustness of fractional ASRatm.

Acknowledgments

This study is funded by the Swiss National Science Foundation Grant No. 200021 135395 ("Towards an improved understanding of the Global Energy Balance: absorption of solar radiation"). We would like to thank Christoph Schär and the Center for Climate Systems Modeling (C2SM) for ongoing support of our work, and Guido Müller and Stefanos Mystakidis for the maintenance of the GEBA. Furthermore, we thank Gert König-Langlo, Miguel Román, David Rutan, Crystal Schaaf, Reto Stöckli, and Jörg Trentmann for providing datasets and useful discussions.
Chapter 6

Solar absorption in the clear & cloudy sky – quantification and attribution
Solar absorption in the clear and cloudy sky – quantification and attribution*

Maria Z. Hakuba¹, Doris Folini¹, Martin Wild¹

Abstract

To expand our previous study (Chapter 5), we estimate atmospheric solar absorption at 432 locations worldwide through combining ground-based measurements of surface solar radiation (SSR) with collocated satellite-derived surface albedo and top-of-atmosphere net irradiance under both, all-sky and clear-sky conditions. Using two ground-based SSR datasets and the CERES EBAF data product, we estimate atmospheric absorption at around 23±2% of TOA incident irradiance under all-sky conditions widely representative of the global scale. The cloud radiative forcing on atmospheric absorption is overall positive, with around 11 Wm⁻² (3.5%) using ground-based data and 5 Wm⁻² (1.5%) in the satellite product. The large discrepancy arises from a potential overestimate in clear-sky atmospheric solar absorption by the CERES EBAF dataset. Nevertheless, the satellite product appears to realistically reproduce the spatial pattern in clear-sky atmospheric absorption as a function of water vapor, surface albedo, and aerosols. While the clear-sky atmospheric absorption is generally lower over the oceans as compared to the land, the atmospheric cloud effect is more pronounced. Low clouds thereby have strong positive effects, while high clouds lead to a near-zero cloud radiative forcing on atmospheric absorption. Within the frame of the CERES products, the latitudinal distribution of atmospheric absorption is smoother under all-sky than under clear-sky conditions, as the cloud radiative forcing acts stronger in the extra-tropics than in equatorial regions, where the fraction of high clouds and the initial clear-sky absorption are the largest. We give some physical explanations, but further research is needed to better understand the spatially variable mechanisms and feedbacks controlling atmospheric solar absorption in the clear and cloudy skies.

*Article in preparation.
¹Institute for Atmospheric and Climate Science, ETH Zurich, Switzerland
6.1 Introduction

One main goal of the present chapter is to spatially expand our previous study [Hakuba et al., 2014a], where we quantified the surface and atmospheric solar absorption over Europe through combining direct measurements of surface solar radiation (SSR) with satellite-derived surface albedo and and top-of-atmosphere (TOA) irradiance. The spatial coverage by surface sites measuring SSR taken from the Baseline Surface Radiation Network (BSRN, [Ohmura et al., 1998]) and the Global Energy Balance Archive (GEBA, [Ohmura et al., 1989]) is rather poor over most continents other than Europe and North America, and a robust global estimate is difficult to obtain. Hence, we furthermore determine the solar energy disposition solely based on the satellite-derived CERES EBAF product [Loeb et al., 2009; Kato et al., 2013] and assess its quality at the surface.

Another focal point of this chapter is to derive the cloud radiative forcing (CRF) on particularly the atmospheric absorption. To do so, we derive continuous records of clear-sky SSR based on work by Long and Ackermann [2000] using the in-situ measurements from 21 BSRN sites and repeat the analysis presented by Hakuba et al. [2014a] under clear-sky conditions.

Although the great debate on “anomalous” cloud absorption came to an end in the early 2000’s [e.g., Li et al., 2003], a large spread in the atmospheric absorption estimates from global climate models still exists [Wild et al., 2013]. The processes underlying cloud absorption are diverse and complex. On the one hand the cloud type is crucial, as it determines both the solar beam’s optical path through the atmosphere and the specific absorption by the cloud’s water droplets and vapor content [Stephens and Tsay, 1990]. On the other hand, feedback processes with other climatic variables, such as aerosols, may enhance or diminish cloud absorption, e.g., via direct or indirect aerosol effects [e.g., Ramanathan et al., 2001; Ramanathan and Carmichael, 2008]. While several studies suggested cloud absorption of up to 30 Wm\(^{-2}\) based on observations that contradicted concurrent climate model integrations [Cess et al., 1995, 1996; Ramanathan et al., 1995; Pilewskie and Valero, 1995; Arking, 1996], many others found it to be negligible and difficult to physically explain [Stephens and Tsay, 1990; Stephens et al., 1996; Li et al., 1995; Li, 2004; Wild, 2000]. Although “anomalous” cloud absorption was disconfirmed to be the cause of model discrepancies in atmospheric solar absorption, consensus about the precise magnitude of cloud absorption has not been reached. Here, we quantify the magnitude of the cloud radiative forcing on atmospheric solar absorption in the climatological annual mean (2000–2010), using most recent data of high quality.

Furthermore, as we find that the fractional atmospheric solar absorption does not vary considerably with latitude over Europe, we will tackle the question on whether this feature holds true on the near-global scale between -60° and 60° North and what the underlying processes are, especially in comparison to the clear-sky state.

The outline is as follows: after presenting the datasets and methods used in Section 6.2, we present our surface and atmospheric absorption estimates representative of the near-global scale beyond Europe (Section 6.3.1) and quantify the cloud radiative forcing at the TOA, the surface, and in the atmosphere (Section 6.3.2). Furthermore, we compare the CERES EBAF surface solar flux under all- and clear-sky conditions to the ground observations (Section 6.3.2) and use the satellite-based data product to study the spatial variability in atmospheric solar absorption and associated cloud effects (Section 6.3.3). At last, we discuss our results in Section 6.4.
6.2 Data and Methods

6.2.1 Ground-based observations

For the technical details on the GEBA and BSRN archives, we refer to Section 5.2.1 in Chapter 5. Here we outline the specifics of the data samples used. The location of the 21 BSRN sites providing SSR records with sufficient data coverage during the study period (2000–2010) are indicated on the map in Figure 6.1 by large pink dots and labeled according to table 6.1. While Hakuba et al. [2014a] used SSR data as measured from pyranometers, we now make use of the more accurate component sum method, i.e., the sum of direct and diffuse SSR as measured from pyrheliometers and shaded pyranometers, respectively [Michalsky et al., 1999]. In cases where one or both of these 1-minute measurements are missing and their sum is not derivable, the pyranometer measurement is used instead. From the minute data, monthly means are computed following the recommendation by Roesch et al. [2011]. Comparing the values of coinciding stations in table 6.1 and table 5.1 in Chapter 5, small discrepancies are noticeable. Main reasons are the switch to the component sum method, the application of a more elaborate quality control after Long and Shi [2008], and the temporal data update at some sites.

The locations of the 411 GEBA sites with sufficient data of good quality during the study period are shown in Figure 6.1 by cyan colored dots. As in Hakuba et al. [2014a], we only use SSR timeseries from the GEBA that are found to be homogeneous during the study period [Hakuba et al., 2013a]. We selected 411 temporally homogeneous (at 99% significance level) GEBA records with monthly data covering at least 4 years of data within the period 2000–2010, less than 30% data gaps, and at least one complete annual cycle. The spatial representativeness of 244 sites as located within the Meteosat disk has been optimized with respect to the CERES 1° grid according to Hakuba et al. [2013a, 2014b].

6.2.2 Clear-sky flux derivation

Using the clear-sky detection and interpolation algorithm [Long and Ackermann, 2000] developed by Charles N. Long at the Pacific Northwest National Laboratory, we derive continuous records of clear-sky SSR from the in-situ measurements obtained at the BSRN sites. This algorithm identifies clear skies using the 1-min measurements of surface downwelling total and diffuse shortwave irradiance to detect clear-sky irradiance measurements, which are used to empirically fit diurnal clear-sky irradiance functions based on the cosine of the solar zenith angle as the independent variable. The coefficients of these functions are interpolated in time until the next clear enough day is detected. These fitted functions produce continuous estimates of clear-sky global, diffuse, and direct component SSR. The estimated clear-sky irradiances are used to estimate the effect of clouds on the downwelling shortwave irradiance as a difference between the measured (all-sky) and clear-sky amounts.

6.2.3 Satellite observations

Most of the satellite-based data products that we employ in the present chapter are introduced in Section 5.2.2, such as the land surface albedo (MODIS, [Schaaf et al., 2002]) and the top-of-atmosphere (TOA) irradiances (CERES EBAF, [Loeb et al., 2012]). Additionally, we will assess and use the CERES EBAF surface product [Kato et al., 2013] more extensively. The surface irradiances are estimated through radiative transfer calculations using satellite-retrieved surface, cloud, and aerosol properties as input [Rutan et al., 2009; Doelling et al., 2013; Kato
et al., 2011, 2013]. Hence, these computed fluxes do not represent a direct measurement but rather a modeled estimate, as the retrieval requires the use of various ancillary datasets and constraints provided by the TOA measurements themselves.

Within the frame of the CERES EBAF dataset, we study the spatial variability in atmospheric absorption and cloud radiative forcing in Section 6.3.3. The CERES mission provides auxiliary datasets, such as MODIS-based cloud properties and aerosol optical thickness, and meteorological assimilation data from the Goddard Earth Observing System (GEOS) Versions 4 and 5 models. We utilize these data to attribute spatial variations in atmospheric absorption under clear- and all-sky conditions. In addition, we make use of aerosol properties from the GOCART aerosol model [Chin et al., 2000, 2002] to qualitatively assess the impact of black carbon on atmospheric absorption.

6.3 Results

6.3.1 Solar absorption under all-sky conditions

BSRN Following Hakuba et al. [2014a], we combine the monthly mean records (2000–2010) of all-sky SSR from 21 BSRN sites with satellite-derived surface albedo (MODIS) and TOA net irradiance (TOAnet, CERES EBAF) to obtain the absorption of solar radiation at the surface (ASRsurf) and within the atmosphere (ASRatm). The locations of the BSRN sites are indicated on the map in Figure 6.1 by large pink dots and labeled according to table 6.1 that presents the corresponding climatological annual mean SSR and absorption estimates. The station-averaged estimates of annual mean ASRsurf and ASRatm under all-sky conditions amount to 139.8 Wm$^{-2}$ (44.9%) and 68.0 Wm$^{-2}$ (21.8%), respectively. The fractional ASRatm estimate of 21.8% obtained here is 0.8% lower than the estimate over Europe [Hakuba et al., 2014a] based on 7 BSRN records that were adjusted to improve their spatial representativeness with respect to the CERES grid [Hakuba et al., 2013b]. Since the majority of sites used here lie outside the spatial domain (Meteosat disk) of the dataset used to analyze the representativeness...
of the surface sites [Hakuba et al., 2014b], only 9 of the 21 records are adjusted. In table 6.1, these, predominantly European sites, are emphasized by asterisks.

The majority of the records originate from the North American continent (9) and Europe (8). The station-averaged fractional ASRatm over the European sites is 23% and 21% considering the North American sites. Not adjusting the representativeness of the BSRN sites, reduces the estimate over Europe by around 1% [Hakuba et al., 2014b]. Whether the discrepancy between the continents is of physical nature or due to the missing adjustment of the North American SSR records is not a priori evident. Nevertheless, many of the North American sites are located in regions that are either elevated (e.g., Boulder) or arid (e.g., Desert Rock), which indeed favors rather low ASRatm.

In Figure 6.2 (top panels) we present the annual cycles of fractional (% solid lines) and absolute (W m\(^{-2}\), dashed lines) ASRatm (blue), ASRsurf (green), and TOAnet (red) under all-sky conditions at four BSRN sites, namely Boulder (BOU), Rock Springs (PSU), Bermuda (BER), and Tateno (TAT). The same plots for all other sites are presented in Figure 6.14 in the Appendix to this chapter. We chose these sites, as they distinguish themselves in terms of climate regime and topographic exposition. At all these sites, the independently derived TOAnet and ASRsurf cycles agree very well, e.g., at Tateno, where the rainy season (May-July) diminishes both TOAnet and ASRsurf noticeably. At Tateno, the fractional ASRatm is at 24% comparably high, which might be caused by the prevalent subtropical and hence humid conditions. Furthermore, the BSRN classifies this site as “urban”, hence we cannot preclude the role of air pollution either. The Boulder site is characterized by dry climate and high altitude (1600 meters), features that indeed are consistent with the low ASRatm estimate of only 15%. Despite the semi-arid conditions at the more northerly located site at Rock Springs, the ASRatm at 23% is significantly enhanced compared to Boulder, likely due to its lower elevation at 400 meters. The very humid climate at Bermuda and more southerly location lead to higher absorption both at the surface and in the atmosphere (24.4%).

Overall, it requires more detailed analysis of the meteorological, surface, and atmospheric conditions to determine at each site the factors contributing to the seasonal variations in the absorption variables. One way to determine the role of clouds is to repeat the present analysis under clear-sky conditions, which we proceed in Section 6.3.2.
GEBA  In the following we use 411 GEBA records (Figure 6.1, cyan colored dots) of sufficient quality to compute the solar absorption partitioning. These records are collocated with 348 CERES grid cells; multiple SSR records per grid cell are averaged prior to their combination with the surface albedo and TOAnet. The corresponding sample-averaged annual mean (2000–2010) estimates of SSR and the absorbed solar fluxes are presented in Table 6.2 based on simple averaging or prior zonal averaging (latitude weighted=latw). The samples involve either all station-grid cell pairs (“all”) or only the grid cells that are detected as “land” using a CERES-based land-sea mask to neglect coastal grid cells.

The scatter in the TOAin and SSR estimates is large as compared to Europe only (Chapter 5) and confirms what we see from the map in Figure 6.1: the spatial coverage by the GEBA-based estimates is poor and biased towards the Northern Hemisphere. By selecting longitudinal and latitudinal boundaries to capture individual continents, such as North America and Asia, we find fractional ASRatm at around 23% over Europe and North America, while Asia yields a mean of almost 26%, which might explain the enhanced sample average of 24%.

In Figure 6.3, we show a histogram of the GEBA-based fractional ASRatm estimates together with the sample mean at 24% (blue solid line) and median at 23.5% (blue dashed). The orange lines indicate the range of 22 to 25% around the median, within which more than half of all values fall. Furthermore, we have indicated the individual BSRN values (black asterisks) together with their median (black dot) at around 22%. Most of the BSRN values lie below the GEBA-based mean and cover the lower tail of the distribution, one value exceeds 26%, while almost 20% of all GEBA-based estimates are larger than 26%. It is worthwhile to note, that while the BSRN sites are predominantly located in very remote and rural regions, many of the measurements taken at the GEBA sites are affected by urban influence [e.g., Wang et al., 2014], which might yield reduced SSR and enhanced ASRatm as compared to less polluted areas.
Table 6.1: Annual mean (2000-2010) estimates of SSR, ASRsurf, ASRatm, TOAnet, TOAin under all-sky conditions at 21 BSRN sites (W m\(^{-2}\)) using MODIS surface albedo and CERES EBAF TOAnet. In parenthesis we give the fractional estimates with respect to TOAin (%). The asterisks indicate flux estimates that are based on SSE-corrected SSR records (section 5.2.1). The majority of sites are located in the USA (9) and in Europe (8). The corresponding clear-sky fluxes are provided in table 6.3 in the Appendix to this chapter.

<table>
<thead>
<tr>
<th>Location</th>
<th>SSR</th>
<th>ASRsurf</th>
<th>ASRatm</th>
<th>TOAnet</th>
<th>TOAin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alice Springs (ASP)</td>
<td>253.9</td>
<td>213.8</td>
<td>82.2</td>
<td>296.4</td>
<td>0.38</td>
</tr>
<tr>
<td>Bermuda* (BER)</td>
<td>186.4</td>
<td>179.9</td>
<td>86.9</td>
<td>266.8</td>
<td>0.48</td>
</tr>
<tr>
<td>Billings (BIL)</td>
<td>194.2</td>
<td>159.2</td>
<td>75.7</td>
<td>234.8</td>
<td>0.48</td>
</tr>
<tr>
<td>Bondville (BON)</td>
<td>171.2</td>
<td>139.8</td>
<td>71.1</td>
<td>210.9</td>
<td>0.51</td>
</tr>
<tr>
<td>Boulder (BOU)</td>
<td>197.3</td>
<td>165.9</td>
<td>49.2</td>
<td>215.1</td>
<td>0.30</td>
</tr>
<tr>
<td>Cabauw* (CAB)</td>
<td>122.8</td>
<td>104.3</td>
<td>64.1</td>
<td>168.5</td>
<td>0.61</td>
</tr>
<tr>
<td>Camborne* (CAM)</td>
<td>127.5</td>
<td>122.4</td>
<td>61.2</td>
<td>183.6</td>
<td>0.50</td>
</tr>
<tr>
<td>Carpentras* (CAR)</td>
<td>163.9</td>
<td>140.6</td>
<td>70.3</td>
<td>210.8</td>
<td>0.50</td>
</tr>
<tr>
<td>Chesapeake Light (CLH)</td>
<td>184.5</td>
<td>176.7</td>
<td>74.6</td>
<td>251.3</td>
<td>0.42</td>
</tr>
<tr>
<td>Desert Rock (DRA)</td>
<td>239.5</td>
<td>193.2</td>
<td>64.6</td>
<td>258.0</td>
<td>0.33</td>
</tr>
<tr>
<td>Fort Peck (FPK)</td>
<td>164.5</td>
<td>128.3</td>
<td>59.5</td>
<td>187.5</td>
<td>0.46</td>
</tr>
<tr>
<td>Goodwin Creek (GWN)</td>
<td>185.2</td>
<td>157.8</td>
<td>82.1</td>
<td>239.8</td>
<td>0.52</td>
</tr>
<tr>
<td>Launder (LAU)</td>
<td>165.1</td>
<td>136.6</td>
<td>52.2</td>
<td>188.7</td>
<td>0.38</td>
</tr>
<tr>
<td>Lerwick* (LER)</td>
<td>85.0</td>
<td>80.2</td>
<td>61.9</td>
<td>142.1</td>
<td>0.77</td>
</tr>
<tr>
<td>Lindenberg* (LIN)</td>
<td>124.0</td>
<td>105.8</td>
<td>61.9</td>
<td>167.8</td>
<td>0.59</td>
</tr>
<tr>
<td>Palaiseau* (PAL)</td>
<td>133.7</td>
<td>111.7</td>
<td>67.2</td>
<td>178.9</td>
<td>0.60</td>
</tr>
<tr>
<td>Payerre* (PAY)</td>
<td>140.8</td>
<td>119.5</td>
<td>60.4</td>
<td>179.9</td>
<td>0.51</td>
</tr>
<tr>
<td>Rock Springs (PSU)</td>
<td>156.2</td>
<td>131.1</td>
<td>75.2</td>
<td>206.2</td>
<td>0.57</td>
</tr>
<tr>
<td>Sioux Falls (SXF)</td>
<td>171.1</td>
<td>134.2</td>
<td>66.7</td>
<td>200.9</td>
<td>0.50</td>
</tr>
<tr>
<td>Tateno (TAT)</td>
<td>156.9</td>
<td>142.5</td>
<td>82.4</td>
<td>224.8</td>
<td>0.58</td>
</tr>
<tr>
<td>Toravere* (TOR)</td>
<td>109.9</td>
<td>92.1</td>
<td>58.2</td>
<td>150.3</td>
<td>0.63</td>
</tr>
<tr>
<td>Station avg.</td>
<td>164.8</td>
<td>139.8</td>
<td>68.0</td>
<td>207.8</td>
<td>0.49</td>
</tr>
</tbody>
</table>

To test the regional representativeness of the GEBA-based estimates, we take the same locations in the CERES EBAF dataset, providing not only the TOA but also the surface solar fluxes (Section 6.2.3), and compare the simple and zonally weighted averages to the global area-weighted mean and some further subsets as listed in table 6.2. By chance, the CERES-based “all latw” average is in quite good agreement with the global mean, at least at the TOA and with respect to ASRatm. Interestingly, in all subsets the fractional ASRatm stays constant at around 23%, which agrees well with the European mean (Chapter 5), but appears to underestimate the GEBA-based sample average of 24% computed here.

### 6.3.2 Clear-sky absorption and cloud radiative effects

Based on the clear-sky detection and interpolation algorithm developed by Charles N. Long (Section 6.2.2), we derived continuous records of clear-sky SSR at the 21 BSRN sites introduced in Section 6.2. Combining these with the surface albedo (MODIS) and clear-sky TOAnet (CERES EBAF), we compute ASRsurf and ASRatm under cloud-free conditions on a monthly mean basis over the period 2000–2010. Thereby, we can estimate the cloud radiative forcing (CRF) on these parameters defined as the difference between the all-sky and clear-sky state.

The annual mean absorption estimates obtained at the BSRN sites under cloud-free conditions are shown in table 6.3 (Appendix to this chapter), the station-averaged estimates of ASRsurf and ASRatm amount to 197 W m\(^{-2}\) (63%) and 57 W m\(^{-2}\) (18%), respectively. In Figure 6.2 (bottom panels), we depict the annual cycles of fractional (solid lines) and absolute (dashed lines) ASRatm (blue), ASRsurf (green), and TOAnet (red) under clear-sky conditions at the four BSRN sites Boulder (BOU), Rocks Springs (PSU), Bermuda (BER), and Tateno (TAT). As compared to the all-sky case (top panels), the absence of clouds appears to smooth
Table 6.2: Annual mean (2000–2010) estimates of SSR, ASRsurf, ASRatm, \( \frac{\text{ASRatm}}{\text{ASRsurf}} \), TOAnet, and TOAin (Wm\(^{-2}\)) averaged over four different GEBAbased subsets. "all": 411 grid cell estimates, "land": 342 grid cell estimates over land only, "latw.": prior zonal averaging is applied. In parenthesis, the estimates are given as fraction of TOAin (%). 244 estimates are based on SSE-corrected GEBA records. Neglecting these corrections, leads to insignificant discrepancies of at most 0.4 Wm\(^{-2}\). Of the CERES EBAF-based estimates (lower part of the table), the first four simulate the GEBA-based subsets above. Below, we present area-weighted averages of the global solar flux estimates and the domain between -60\(^\circ\) to 60\(^\circ\) North as studied in Section 6.3.3.

<table>
<thead>
<tr>
<th>GEBA subsets</th>
<th>SSR</th>
<th>ASRsurf</th>
<th>ASRatm</th>
<th>TOAnet</th>
<th>( \frac{\text{ASRatm}}{\text{ASRsurf}} )</th>
<th>TOAin</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>161.6</td>
<td>140.3 (43.8)</td>
<td>76.9 (24.0)</td>
<td>217.2</td>
<td>0.55</td>
<td>320.7</td>
</tr>
<tr>
<td>all latw.</td>
<td>176.2</td>
<td>154.5 (45.6)</td>
<td>83.0 (24.5)</td>
<td>237.7</td>
<td>0.54</td>
<td>339.1</td>
</tr>
<tr>
<td>land</td>
<td>158.2</td>
<td>133.8 (42.4)</td>
<td>75.3 (23.9)</td>
<td>209.2</td>
<td>0.56</td>
<td>315.4</td>
</tr>
<tr>
<td>land latw.</td>
<td>171.8</td>
<td>144.7 (43.8)</td>
<td>80.2 (24.3)</td>
<td>225.0</td>
<td>0.55</td>
<td>330.6</td>
</tr>
<tr>
<td>CERES EBAF subsets</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>all</td>
<td>164.1</td>
<td>142.1 (44.3)</td>
<td>73.8 (23.0)</td>
<td>217.2</td>
<td>0.52</td>
<td>320.7</td>
</tr>
<tr>
<td>all latw.</td>
<td>180.8</td>
<td>158.3 (46.7)</td>
<td>77.8 (22.9)</td>
<td>237.7</td>
<td>0.49</td>
<td>339.1</td>
</tr>
<tr>
<td>land</td>
<td>160.4</td>
<td>135.4 (42.9)</td>
<td>72.2 (22.9)</td>
<td>209.2</td>
<td>0.53</td>
<td>315.4</td>
</tr>
<tr>
<td>land latw.</td>
<td>175.6</td>
<td>147.7 (44.7)</td>
<td>75.1 (22.7)</td>
<td>225.0</td>
<td>0.51</td>
<td>330.6</td>
</tr>
<tr>
<td>glo</td>
<td>186.8</td>
<td>162.7 (47.8)</td>
<td>77.8 (22.9)</td>
<td>240.5</td>
<td>0.48</td>
<td>340.1</td>
</tr>
<tr>
<td>glo land</td>
<td>187.2</td>
<td>139.4 (42.9)</td>
<td>73.9 (22.7)</td>
<td>213.2</td>
<td>0.53</td>
<td>325.2</td>
</tr>
<tr>
<td>6060</td>
<td>198.8</td>
<td>179.7 (49.6)</td>
<td>83.5 (23.1)</td>
<td>263.3</td>
<td>0.47</td>
<td>361.6</td>
</tr>
<tr>
<td>6060 land</td>
<td>204.4</td>
<td>163.5 (45.5)</td>
<td>83.4 (23.2)</td>
<td>246.8</td>
<td>0.51</td>
<td>359.2</td>
</tr>
</tbody>
</table>

the seasonal cycles, the remaining variations can be attributed to variations in surface albedo, atmospheric composition, and solar zenith angle. All other sites’ annual cycles under clear-sky conditions are provided in Figure 6.15 in the Appendix to this chapter.

We compute the cloud radiative forcing (CRF) on TOAnet, ASRsurf, and ASRatm as the difference between the all-sky and clear-sky state. The bar plots in Figure 6.4 depict the cloud radiative forcing on TOAnet (top left), ASRsurf (top right), and ASRatm (bottom left) in Wm\(^{-2}\) at each BSRN location (light colors) and in comparison to the CERES EBAF-derived cloud forcing on ASRsurf and ASRatm (dark colors) at the same locations. While TOAnet at these sites is reduced by on average -46 Wm\(^{-2}\) (-15%), the cloud forcing on ASRsurf as derived from the BSRN data is even more pronounced at around -57 Wm\(^{-2}\) (-19%), ranging between -20 Wm\(^{-2}\) (-6%, Desert Rock) and -87 Wm\(^{-2}\) (-25.5%, Tateno). Consequently, ASRatm is enhanced in the cloudy sky by on average +11 Wm\(^{-2}\) (3.5%), ranging between +0.6 Wm\(^{-2}\) (+0.2%, Lauder) and +21 Wm\(^{-2}\) (+6%, Bermuda). As expected, both the BSRN-based and the CERES EBAF-derived estimates point to a negative CRF at the surface and at the TOA, while the CRF on ASRatm is positive. The satellite-derived products yield thereby a substantially weaker forcing on ASRatm of on average +3.6 Wm\(^{-2}\) (1.2%).

The CRF as just dealt with is affected by the frequency of cloudy states that varies from site to site. A measure of cloud absorption that cancels the cloud frequency dependence is the forcing ratio \( R \) (equation 1.3) that relates the CRF at the surface to the CRF at TOA [e.g., Li and Leighton, 1993; Ramanathan et al., 1995]. If the surface forcing exceeds the forcing at TOA and the relation becomes \( R > 1 \), the presence of clouds yielded an increase in ASRatm at this site. Our analysis (Figure 6.4, bottom right) based on the BSRN data (light orange) suggests an \( R \) value of on average 1.25, which clearly points to significant cloud absorption,
ranging between 1 and 1.4. The CERES EBAF average is at 1.1 substantially lower, ranging between 0.9 and 1.25. In Section 6.4, we discuss the existing literature on the magnitude of cloud absorption and put our results into perspective.

Towards explaining the disagreement in CRF between BSRN and CERES EBAF: Comparison of surface solar flux

The all-sky and clear-sky SSR fluxes provided by the CERES EBAF product are biased with respect to the ground-based measurements, which largely explains the difference in cloud radiative forcing at the surface and in the atmosphere. In the following, we briefly present the comparison of the satellite-derived all-sky SSR to the measurements from the GEBA and BSRN, and the clear-sky flux to the records based on the BSRN observations.

GEBA The monthly mean difference (2000–2010) in all-sky SSR between CERES EBAF and the GEBA data is at +2.5 Wm$^{-2}$ in contrast with recent results by Kato et al. [2013], who found a negative bias of -1.7 Wm$^{-2}$ as compared to 24 land surface sites (majority located
in Northern America). The root-mean-squared-error (RMSE) is at 11 Wm\(^{-2}\) only slightly larger than the estimate by Kato et al. [2013] at 8 Wm\(^{-2}\). Looking at the map of annual mean differences (CERES EBAF minus GEBA) in Figure 6.5, we see a quite distinct regional pattern with largest positive biases occurring over Asia, except for Japan where CERES EBAF slightly underestimates the all-sky SSR. Hence, the mean bias strongly depends on the data sample used in this comparison and changes the sign when considering the sites in Europe [Hakuba et al., 2014b] and America only. The bias in ASRsurf is at +1.8 Wm\(^{-2}\) slightly smaller than in SSR, hence it is offset by a small discrepancy in the surface albedos used. Indeed, the MODIS-based surface albedo at these locations is at 0.153 somewhat darker than the CERES EBAF albedo at 0.16 (RMSE = 0.02).

**BSRN**  Contrasting results we obtain when comparing CERES EBAF with the substantially smaller dataset of the BSRN measured all-sky and derived clear-sky SSR (Figure 6.6). Under both, all- and clear-sky conditions, CERES EBAF now underestimates the surface flux. The mean bias in all-sky SSR is thereby at -1.5 Wm\(^{-2}\) (RMSE = 5 Wm\(^{-2}\)) of similar absolute magnitude as the bias obtained with respect to the GEBA data, but of opposite sign. The negative bias in clear-sky SSR is at -9.4 Wm\(^{-2}\) (RMSE = 4 Wm\(^{-2}\)) significantly larger, indicating a higher clear-sky ASRatm in the EBAF dataset than the BSRN data would suggest and may explain the discrepancy in cloud radiative forcing (Section 6.3.2) to a large degree.

When comparing the BSRN-based and EBAF-based timeseries of deseasonalized monthly anomalies, we find that at most sites, the temporal variability under all-sky conditions agrees very well, while under clear-sky conditions there is a distinct mismatch in both inter- and intra-annual variability (not shown). In 2006, the aerosol source in the CERES EBAF surface product was changed from one MODIS collection to another, which strongly affected trends in clear-sky SSR in some regions over land [NASA LARC, 2014] and might partly explain the discrepancies. Still, issues in the retrieval of both the BSRN-based and the EBAF-based data products as well as the role of the clear-sky definition (Section 1.2.1) need to be further investigated in order to more comprehensively explain these discrepancies.
6.3 RESULTS

Figure 6.6: Left: scatter of annual mean (2000–2010) all-sky SSR at 21 BSRN sites (x axis) versus CERES EBAF (y axis). $r^2 = 0.98$, slope = 0.98. Mean bias = -1.5 Wm$^{-2}$, RMSE = 5 Wm$^{-2}$. Right: The same as left but for clear-sky SSR. $r^2 = 0.97$, slope = 1.01. Mean bias = -9.4 Wm$^{-2}$, RMSE = 6 Wm$^{-2}$. The black solid line represents the 1:1 line, in red the linear regression line, the dashed black lines represent the $\pm 1\sigma$ lines of the BSRN sample.

6.3.3 Attribution of spatial variations in atmospheric solar absorption

Over Europe, we found the fractional ASRatm (% of TOAin) under all-sky conditions to be largely unaffected by variations in latitude, remaining nearly constant at the regional mean of 23% [Hakuba et al., 2014a]. Here, we use the satellite-derived CERES EBAF products to examine whether and why this spatial pattern might hold on the near-global scale between -60° and 60° North. In Figure 6.7 we see that (1) the zonally averaged fractional all-sky ASRatm (blue line) does vary with latitude. It peaks in the tropics and levels off towards the poles. However, (2) in line with the findings over Europe, the values remain nearly constant at 23% in the extratropics. (3) Under clear-sky conditions (orange line) the fractional ASRatm is not only reduced, but the latitudinal distribution is also more perturbed. Hence, clouds must play a crucial role in smoothing the latitudinal distribution of fractional ASRatm under all-sky conditions.

We use the CERES EBAF dataset to investigate the spatial variability in fractional clear-sky ASRatm with respect to variations in the water vapor, surface albedo, and aerosol fields, the key parameters in modulating the ASRatm under cloud-free conditions (Chapter 1). In a next step, we explore the cloud radiative forcing of different cloud types to explain their smoothing effect on the latitudinal distribution of fractional ASRatm under all-sky conditions.

Clear-sky atmospheric absorption

As shown in Figure 6.8 (top), the CERES EBAF-derived clear-sky fractional ASRatm is very low over subtropical dry regions and elevated terrain, and maximizes in tropical Africa, South America, and Southeast Asia, particularly over land. From the water vapor map (Figure 6.8, second from top), we see that the humidity distribution alone cannot fully explain this pattern. There are several lines of evidence that the surface albedo (Figure 6.8, third from top) plays a significant role in creating land-sea contrasts in the clear-sky ASRatm. Although we find an exponential relationship between water vapor (wv) and clear-sky ASRatm (Figure 6.9, left) that is in line with previous studies (Figure 1.5) presented in Chapter 1, the curves take different shapes over the oceans (Figure 6.9, left, blue dashed line) and over the land (black dashed
lines). Evidently, the clear-sky ASRatm is systematically enhanced over the land surfaces of brighter albedo (yellow-reddish color coding) as compared to the darker oceans.

Figure 6.9 (right) shows a scatter plot of the annual mean surface albedo values (x axis) in each grid box of our domain versus the fractional clear-sky ASRatm (y axis). The values are color-coded with respect to 10 bins of water vapor amount in centimeters (cm) as indicated by the colorbar. We assume the relationship between surface albedo and clear-sky fractional ASRatm to be linear (cf. $\text{ASRatm} \propto \text{albedo} \cdot e^{-\tau_{wv}}$ with $\tau_{wv} = \text{const.}$) and regress the binned values. As expected, the surface albedo and ASRatm are positively correlated and the slopes of the binned regression lines increase exponentially with water vapor load (Figure 6.9, right). While for water vapor loads between 1.5 and 2 cm (≈20 kg m$^{-2}$) the ASRatm increases by around 1% per 0.1 change in surface albedo, the change for higher water vapor loads between 4 and 4.5 cm is up to 3.5%, which explains the enhanced land-sea contrast in very humid regions like the tropics (cf. Figures 6.8).

In Chapter 1 we outlined that absorbing aerosols like black carbon play a vital role in enhancing the clear-sky ASRatm. Although the water vapor loads in equatorial Africa and South East Asia are lower than in equatorial South America, the clear-sky ASRatm is of similar or even slightly higher magnitude. Large black carbon concentrations are highly localized and indeed confined to the regions of these ASRatm maxima over Africa and Asia (cf. Figure 1.4, left). Chung et al. [2005] derived black carbon absorption of up to 16 Wm$^{-2}$ in these regions, equivalent to almost 5% of TOAin. Although the MODIS-derived AOD input data to the CERES product (Figure 6.8, fourth from top) do not exclusively show the spatial distribution of absorbing aerosols, they still indicate where enhanced aerosol absorption may very likely occur. Determined from another independent source – the GOCART aerosol model data V006 [Chin et al., 2000, 2002] – the absorption optical depth of black carbon (at 550nm) shown in Figure 6.8 (fifth from top) is in good agreement with Figure 1.4 (left) by Chung et al. [2005] and the ASRatm maxima in our Figure 6.8 (top).

All three parameters – water vapor, AOD, surface albedo – but especially the latter two, show higher mean values over the Northern than over the Southern Hemisphere (Figure 6.16), likely driven by the uneven distribution of (populated) land masses. This hemispheric asymmetry is reflected by the zonal distribution of clear-sky ASRatm (Figure 6.7, orange line).
**Figure 6.8:** Top: Map of annual mean (2000–2010) fractional clear-sky ASR$_{atm}$ derived from CERES EBAF (%). Second from top: Integrated water vapor as input to CERES EBAF products (cm). Third from top: surface albedo derived from CERES EBAF surface product. Fourth from top: MODIS-derived AOD (550nm), ancillary data to CERES EBAF. Bottom: black carbon absorption optical depth (550nm) based on GOCART aerosol transport model [Chin et al., 2002].
Cloud radiative effect on atmospheric absorption

The climatological annual mean (2000–2010) cloud radiative forcing (CRF) on ASRatm defined as the difference between the all-sky and clear-sky fractional ASRatm (Figure 6.10), is overall positive except for the tropics over land, East China, Northern India, and some spots in Europe. The presence of clouds enhances the fractional ASRatm in this domain (-60° and 60° North) by on average +1.5% (5 Wm⁻²). A land-sea contrast is thereby evident with a CRF at +1% (3 Wm⁻²) over land and +1.7% (6 Wm⁻²) over the oceans.

Since the cloud absorption strongly depends on the cloud type as described in Chapter 1, we use the information on cloud-top-pressure (CTP) and cloud fraction as provided by the CERES SYN1deg product [Kato et al., 2011] to distinguish between cloud types and their impact on ASRatm. The cloud classification is solely based on the CTP, and so far we do not involve cloud optical properties that strongly affect the cloud absorbance as well. Within the frame of this data product, low clouds range between the surface and 700 hPa, low-to-mid clouds range between 700–500hPa, mid-to-high clouds range between 500–300 hPa, and the CTP of high clouds exceeds 300 hPa. Figure 6.17 in the Appendix to this chapter depicts the annual mean (2000–2010) maps of the cloud fraction at these four CTP increments, but in the following we will focus on the low (Figure 6.17, top) and high (Figure 6.17, bottom) clouds predominantly. While the cloud fraction of low clouds maximizes over the oceans in the sub- and extra-tropics, high clouds are mostly located in the tropics. From these maps (Figure 6.17) and Figure 6.10, we can see that low clouds predominantly enhance ASRatm, while the high clouds in the tropics have weaker or even negative effects, especially over land.

To quantify the CRF of low and high clouds separately, we identify grid cells in which the fraction of the respective cloud type exceeds a certain threshold. The histograms in Figure 6.11 are based on those CRF values between -60° to 60° North that coincide with cloud fractions of low clouds exceeding 20% (top) and cloud fractions of high clouds exceeding 30% (bottom) considering grid cells over land (left) and over the oceans only (right). The low clouds enhance the fractional ASRatm on average (red line) by +2% over the oceans (right) and by +1.3% over
6.3 RESULTS

Figure 6.10: Map between -60° to 60° North of annual mean (2000–2010) cloud radiative forcing (CRF) = fractional all-sky ASR_{atm} minus fractional clear-sky ASR_{atm} (%).

land (left). High clouds (bottom) increase ASR_{atm} over the oceans only slightly by +0.2% and decrease ASR_{atm} over land by on average -0.7%. All these CRF mean values are significantly different from zero (99% level, t-test).

Next, we ask how the CRF changes with increasing fraction of low and high clouds, respectively. The scatter plots in Figure 6.12 depict the relationship between the cloud fraction (x axis) and CRF (y axis) for low (top) and high clouds (bottom) over land (left) and ocean (right). Looking at the ocean (right) a distinct positive correlation (r²=0.6) between the fraction of low clouds and CRF is evident. The slope of the regression line indicates an increase in ASR_{atm} by +0.6% per 10% change in cloud fraction. Considering the high clouds, there is a clear negative correlation (r²=-0.4, -0.7% per 10%) between the cloud fraction and CRF, but the CRF rarely turns negative.

Considering the land points only (Figure 6.12, left), the large data scatter leads to a very low correlation between the cloud fraction of low clouds and CRF (r²=0.01) and insignificant relationship between the variables. Considering the high clouds, the negative relationship is more distinct (r²=-0.2, -0.5% per 10%) and significant. The colors furthermore indicate the magnitude of the clear-sky ASR_{atm} at the scattered data points; over land a larger spread in clear-sky ASR_{atm} is evident as compared to the ocean and for values exceeding approximately 26%, the CRF becomes negative independent of the cloud amount and type.

From this analysis and the maps in Figures 6.10 and 6.8, we see that clouds decrease ASR_{atm} in regions where the clear-sky ASR_{atm} is initially high. It is hence no surprise that we find a significant negative correlation (r²=0.5) between the CRF and clear-sky ASR_{atm} (not shown) indicating a decrease of -0.4% in CRF with a 1% increase in clear-sky ASR_{atm}.

The evident land-sea contrasts in CRF, we at least partly attribute to surface albedo feedbacks. It appears that over the oceans, the specific cloud absorption and the effect of reduced pathlength due to high clouds (see Chapter 1) cancel out, which leads to a near-zero CRF. Over brighter surfaces, high clouds do not only reduce the optical path for the downwelling radiation but also suppress the atmospheric absorption of upwelling radiation as reflected by the surface. Hence, over a surface of high reflectivity, especially in the near-infrared as typical for vegetated surfaces [Melinova, 1973], a humid clear-sky atmosphere appears to be more efficient in absorbing solar radiation than the cloudy sky. Low clouds do not reduce the optical pathlength as much as high clouds do. Hence, low clouds overall exhibit a positive CRF on atmospheric
Figure 6.11: Histograms of CRF on fractional ASRatm (%) due to cloud fractions of low clouds exceeding 20% over land in our study domain between -60° to 60° North (top left). The same but over the oceans (top right). CRF due to fractions of high clouds exceeding 30% over land (bottom left) and over the oceans (bottom right). The black dashed line indicates CRF=0, the red line represents the sample mean, the blue line the sample median.

absorption over both, land and ocean. Still, the positive CRF due to low clouds over the oceans is somewhat enhanced compared to the land. Likely, the low clouds over the darker ocean surface lead to additional upwelling solar radiation that is partly absorbed on its way back to space.

Independent of cloud type, the CRF is small or even negative in regions where the clear-sky ASRatm is comparably high and exceeds 26%. This is the case in very humid (e.g., tropics) and highly polluted regions (e.g., East China, Northern India, equatorial Africa). Nevertheless, equally high humidity or aerosol loads over the ocean yield lower clear-sky ASRatm than over land, which is likely driven by surface albedo feedbacks discussed in the previous paragraph.

**Latitudinal distribution of fractional atmospheric absorption**

To synthesize the results of this section and to attribute the latitudinal variability in ASRatm to the physical relationships we found according to the CERES EBAF data products, we present in Figure 6.13 the latitudinal mean distributions (2000–2010) of fractional ASRatm under all-sky conditions (blue line) and clear-sky conditions (orange line), considering both land and ocean between -60° to 60° North (top), only land (middle), and only the oceans (bottom). The shading indicates the spatial scatter around the mean in terms of ±1σ.

From this figure we clearly see that the zonal mean distribution of all-sky ASRatm (blue line, top panels) is not only enhanced compared to the clear-sky conditions (orange line), but
also more uniform, especially over the mid-latitudes. Furthermore, a certain hemispheric asymmetry is visible, particularly under clear-sky conditions, which we attribute to enhanced water vapor (over oceans) and aerosol loads (land+ocean), and enhanced surface albedo over the continents in the Northern hemisphere (Figure 6.16).

Over land, substantial altitude effects (Chapter 5) can lead to very low clear-sky ASRatm over high topography, such as the Andes and the Tibetan plateau (cf. Figure 6.8, top). Surface albedo and aerosol effects furthermore lead to maxima in tropical and Asian regions. Hence, considering the land masses only (middle), the zonal mean distribution is more complex and widespread than over the oceans (bottom), the latter dominating the global picture (top). Over the oceans, the all-sky ASRatm is more systematically enhanced throughout the latitudes, while over land, the magnitude of the atmospheric cloud forcing is overall diminished and even turns negative in the tropics due to predominantly high clouds.

The coverage by low clouds, which we showed to exhibit a significant positive forcing on ASRatm, increases polewards (not shown). The high clouds in the tropics have only little or negative impact on ASRatm. These two opposing effects, caused by the different cloud types and land-sea contrasts, lead to a smoothing of the latitudinal mean distribution of fractional ASRatm under all-sky conditions.

Figure 6.12: Annual mean (2000–2010) fraction of low clouds (%; x axis) versus CRF on fractional ASRatm (%; y axis) over land (top left) and over the oceans (top right). The same for high cloud fractions in the bottom panels including linear regression lines (black solid). The coloring indicates the magnitude of fractional clear-sky ASRatm (%). The study domain is constrained to -60° to 60° North.
6.4 Discussion and conclusions

In order to spatially expand the quantification of surface and atmospheric solar absorption beyond Europe (Chapter 5), we have now included 21 BSRN and 411 GEBA sites providing surface solar radiation (SSR) measurements between -55° and 68° North. The vast majority of sites are thereby located in the Northern Hemisphere as the coverage by surface sites over continents other than Europe, North America, and Asia is rather poor.

While the BSRN-based station average yields annual mean (2000–2010) fractional atmospheric absorption (ASRatm) of around 22%, the GEBA sample suggests a higher value of around 24%, driven by particularly high estimates over Asia of on average 26%. We test the regional representativeness of our GEBA sample using the CERES EBAF surface and TOA products and find the ASRatm estimate to be widely representative for the global scale. While the CERES EBAF-derived ASRatm agreed very well with the GEBA-based estimates over Europe (Chapter 5), the value at 23% derived here lies in between the BSRN and GEBA-based estimates and is very robust throughout multiple sub-samples that we drew from it.

Following Wang et al. [2014], a substantial amount of GEBA sites is located in urbanized regions, hence strongly polluted areas in which SSR measurements are likely diminished [e.g., Alpert et al., 2005] and the ASRatm enhanced. On the contrary, most of the BSRN sites do not suffer from this urban influence as many of them are located in remote areas, including coastlines, mountains, and islands. This would mean that the CERES EBAF estimate at 23% represents a reliable middle course. Hence, relying on the CERES EBAF data and using the BSRN-based and GEBA-based estimates as upper and lower limits, we obtain a global mean fractional ASRatm estimate of 23±2% equivalent to 78±7 Wm⁻², which is in very good agreement with recent global mean estimates by Trenberth et al. [2009] and Wild et al. [2013]. On the other hand, the GEBA-based estimate of 83 Wm⁻² (24%) is in remarkable agreement with Li and Leighton [1993] and Li et al. [1997], and a more recent study by Kim and Ramanathan [2012], in which a global mean estimate was obtained by integrating BSRN and CERES EBAF observations with a comprehensive set of satellite-derived atmospheric and surface optical properties using the Monte Carlo Aerosol-Cloud-Radiation model (MACR).

Based on the clear-sky detection and interpolation algorithm by Long and Ackermann [2000], we derived continuous records of clear-sky SSR at the 21 BSRN sites and determined an annual mean (2000-2010) cloud radiative forcing on atmospheric absorption of on average +11 Wm⁻² (3.5% of TOA incident). The CERES EBAF data product suggests a cloud forcing of +5 Wm⁻² (1.5%) in the global mean and underestimates the BSRN values by around 7 Wm⁻², which arises from a strong underestimate in clear-sky SSR. Kim and Ramanathan [2008] determined global mean cloud absorption using the sophisticated MACR model at +7 Wm⁻², which is of similar magnitude. Both our values are reasonable in the sense that neither points to ”anomalous“ cloud absorption (up to 30 Wm⁻², R=1.5) as formerly assumed but disproved [e.g., Stephens and Tsay, 1990; Cess et al., 1995; Arking, 1996; Li et al., 1997].

The question whether the disagreement between the BSRN-based and EBAF-based clear-sky SSR is of physical nature or due to methodological and retrieval issues is yet to be answered. Several explanations can be suggested. Main issues certainly lie in the computation of the clear-sky flux and detection of cloud-free scenes in both the Long and Ackermann [2000] algorithm and the satellite retrieval. While the estimation from surface measurements relies on empirical relationships, the CERES EBAF clear-sky fluxes undergo a more complex chain of retrieval steps, involving radiative transfer modeling and the adjustment to the TOA fluxes within the input datasets’ uncertainties [Kato et al., 2011, 2013]. Also the role of cloud detection to derive the clear-sky scenes needs to be discussed. On the one hand, small cloud
Figure 6.13: Zonal averages of annual mean (2000–2010) all-sky (blue) and clear-sky (orange) fractional ASR$_{atm}$ (%) over land + oceans (top), only land (middle), only oceans (bottom). The shading indicates the spatial scatter around the mean in terms of $\pm$1$\sigma$. 
amounts often remain undetected due to scene identification problems, which strongly depend on the satellite instrument’s field of view [Ackerman et al., 1998; Stubenrauch et al., 2013]. Another problem is certainly the difficulty of detecting clouds over bright surfaces [Rossow and Garder, 1993], which can lead to a faulty pixel classification as well. Depending on the surface and cloud properties, the satellite-derived clear-sky SSR could then be biased either towards an underestimate (small clouds) or overestimate (bright surface).

Similar as under all-sky conditions, but likely less critical, is the spatial representativeness of the surface sites being compared to or combined with the gridded CERES data (Chapters 2 and 3), since variations in topography and aerosol might lead to a mismatch between the point measurement and the area mean of the collocated grid cell. To assess the site representativeness for SSR under clear-sky conditions, we would need a high-resolution satellite-based dataset that fully resolves variations in these parameters, which is not yet provided by the Meteosat-based dataset employed in Chapters 2 and 3.

In the context of this spatial-scale disparity, another possible source of uncertainty should be mentioned, which is related to 3D cloud effects [e.g., Stephens and Tsay, 1990; Barker et al., 1999; Fu et al., 2000]. Multiple scattering in broken cloud cover and the horizontal transport of photons into the instrument’s field of view could potentially enhance a ground-based clear-sky observation as compared to the estimate derived in a larger-scale satellite footprint that might suffer from the insufficient representation of these effects. The quantification of these effects is beyond the scope of this study, but should be kept in mind for future applications.

Although the CERES EBAF underestimates the clear-sky SSR as compared to the BSRN-derived dataset, it appears to realistically represent the spatial pattern in annual mean clear-sky ASRatm as a function of the input water vapor distribution, surface albedo, and aerosols. We find that while the clear-sky atmospheric absorption is generally lower over the oceans as compared to the land, the atmospheric cloud effect is more pronounced. As expected, low clouds feature stronger positive effects – on the order of +2% – than high clouds that exhibit a near-zero cloud radiative forcing and even decrease the absorption over tropical land masses, where the absorption under clear-sky conditions appears to be more efficient. To better understand potential feedbacks with respect to the surface albedo and aerosols, the land-sea contrast in absorption and cloud forcing, as well as the cloud type dependencies, we see the need to involve additional independent datasets and modeling approaches.

In line with Li et al. [1995], the zonal mean distribution of fractional atmospheric absorption remains nearly constant at its annual mean value of 23% (Li et al. [1995] found 24%). Nevertheless, some variations are visible, which are mostly driven by the humidity distribution, i.e. the fractional atmospheric absorption peaks in the tropics and slightly decays in the subsidence zones. However, these variations are more pronounced under clear-sky conditions, as clouds tend to smooth the latitudinal distribution. While Li and Moreau [1996] found strongest atmospheric cloud effects in heavily polluted regions, in both the mid-latitudes and tropics, the CERES EBAF data demonstrate the opposite, with weaker atmospheric cloud effects in regions where the clear-sky absorption is initially high, such as the tropics or polluted areas in Asia. Overall, the positive cloud forcing on atmospheric solar absorption acts stronger in the extratropics where predominantly lower clouds prevail, while high clouds in the tropics have no or even negative impact. Together, this leads to a smoothing of the zonal mean distribution of atmospheric solar absorption under all-sky conditions.
6.4 Discussion and Conclusions

Acknowledgments

This study is funded by the Swiss National Science Foundation Grant No. 200021 135395 (“Towards an improved understanding of the Global Energy Balance: absorption of solar radiation”). We would like to thank Christoph Schär and the Center for Climate Systems Modeling (C2SM) for ongoing support of our work. In particular, we thank Charles N. Long and Guido Müller for the close collaboration in setting up the RFA analysis tools at ETH and for the continued support in the post-processing of the BSRN datasets.
6.A  Appendix to Chapter 6

6.A.1  Supplementary Table

Table 6.3: Annual mean (2000–2010) estimates of SSR, ASRsurf, ASRatm, TOAnet, TOAin under clear-sky conditions at 21 BSRN sites (Wm$^{-2}$) using MODIS surface albedo and CERES EBAF TOAnet. In brackets we give the estimates as fraction of TOAin (%). The majority of the sites are located in the USA (9) and in Europe (8).

<table>
<thead>
<tr>
<th>Station</th>
<th>SSR</th>
<th>ASRsurf</th>
<th>ASRatm</th>
<th>TOAnet</th>
<th>ASRsurf in TOAnet</th>
<th>TOAin</th>
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<tr>
<td>Alice Springs (ASP)</td>
<td>291.6</td>
<td>244.6 (63.7)</td>
<td>74.1 (19.3)</td>
<td>318.7 (83.0)</td>
<td>0.30</td>
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<td>65.7 (18.4)</td>
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<td>0.26</td>
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<td>Billings (BIL)</td>
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<td>207.5 (60.7)</td>
<td>65.9 (19.3)</td>
<td>273.4 (80.0)</td>
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<td>243.2</td>
<td>198.5 (61.0)</td>
<td>57.2 (17.6)</td>
<td>255.6 (78.5)</td>
<td>0.28</td>
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<td>214.5 (65.9)</td>
<td>46.3 (14.2)</td>
<td>260.8 (80.1)</td>
<td>0.22</td>
<td>325.6</td>
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<td>166.9 (60.4)</td>
<td>50.2 (18.2)</td>
<td>217.1 (78.6)</td>
<td>0.30</td>
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<td>193.6 (68.8)</td>
<td>52.7 (18.7)</td>
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<td>252.2 (81.8)</td>
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<td>Chesapeake Light (CLH)</td>
<td>239.3</td>
<td>241.6 (70.0)</td>
<td>65.3 (19.9)</td>
<td>304.5 (89.1)</td>
<td>0.27</td>
<td>341.8</td>
</tr>
<tr>
<td>Desert Rock (DRA)</td>
<td>263.8</td>
<td>212.9 (62.3)</td>
<td>59.4 (17.4)</td>
<td>272.3 (79.7)</td>
<td>0.28</td>
<td>341.9</td>
</tr>
<tr>
<td>Fort Peck (FPE)</td>
<td>215.4</td>
<td>167.9 (57.8)</td>
<td>52.4 (18.0)</td>
<td>220.0 (75.8)</td>
<td>0.31</td>
<td>290.5</td>
</tr>
<tr>
<td>Goodwin Creek (GCR)</td>
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<td>217.2 (62.2)</td>
<td>68.7 (19.7)</td>
<td>286.0 (81.9)</td>
<td>0.32</td>
<td>349.4</td>
</tr>
<tr>
<td>Lauder (LAU)</td>
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<td>192.4 (63.1)</td>
<td>51.6 (16.9)</td>
<td>244.1 (80.1)</td>
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<td>304.8</td>
</tr>
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<td>271.7</td>
</tr>
<tr>
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<td>172.0 (59.2)</td>
<td>55.0 (19.0)</td>
<td>227.1 (78.2)</td>
<td>0.32</td>
<td>290.4</td>
</tr>
<tr>
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<td>55.5 (18.5)</td>
<td>238.1 (79.5)</td>
<td>0.30</td>
<td>299.5</td>
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<tr>
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<td>57.9 (17.8)</td>
<td>260.9 (80.1)</td>
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<td>325.6</td>
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<td>57.6 (18.4)</td>
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<td>Tateno (TAT)</td>
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<td>229.8 (67.2)</td>
<td>62.9 (18.4)</td>
<td>292.8 (85.6)</td>
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<tr>
<td>Toravere (TOR)</td>
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<td>242.8</td>
</tr>
<tr>
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<td>57.0 (18.3)</td>
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6.A.2 Supplementary Figures

Figure 6.14: Mean annual cycles (2000-2010) of absolute (dashed lines) and fractional (with respect to TOAin, solid lines) TOA\textit{net} (red), ASRsurf (green), and ASRatm (blue) under all-sky conditions at the 17 BSRN sites (table 6.3) not shown in Figure 6.2. The shading indicates the ±1σ scatter across years.
Figure 6.15: Same as Figure 6.14 but for clear-sky conditions.
Figure 6.16: Zonal distribution of integrated water vapor (cm, top), AOD (middle), and surface albedo (bottom) between -60° to 60° over land only (orange), oceans (blue), and land+oceans (black).
Figure 6.17: Maps of annual mean (2000–2010) cloud fraction (%) of low clouds at cloud top pressures between the surface and 700 hPa (top), of low-to-mid clouds ranging between 700–500 hPa (second from top), mid-to-high clouds ranging between 500–300 hPa (third from top), and high clouds exceeding 300 hPa (bottom). Data are taken from the CERES SYN1deg data product [Kato et al., 2011]
Chapter 7

Conclusions and Outlook

Combining direct radiation measurements from space and ground, we quantified present day (2000–2010) mean-state surface and atmospheric solar absorption to establish a key reference for the validation of climate models and satellite products. To obtain climatological best-possible estimates, we used data of highest possible quality and scrutinized the attached uncertainties (Chapter 5). We thereby largely focused on Europe, the region in the world with the highest density of surface solar radiation in-situ measurements on the continental scale. To reduce uncertainties, we objectively selected the surface observations based on their timeseries’ temporal homogeneity (Chapter 2) and studied their spatial representativeness with respect to the gridded satellite product to account for scale-induced collocation errors (Chapter 3 and 4). Finally, we quantified the cloud radiative effects at the surface and in the atmosphere, and attribute spatial variations in atmospheric absorption to spatial variations in surface albedo, atmospheric composition, and particularly clouds on the near-global scale (Chapter 6). In the following, we summarize the chapters’ main findings, their limitations, and potential future prospects.

Chapter 2

The temporal homogeneity of a timeseries is not only crucial in trend analysis, but also in model validation and the computation of climatologies. In this Chapter, we exemplified the use of four absolute homogeneity tests to statistically determine the temporal quality of 172 European surface solar radiation (SSR) records over the period 2000–2007 and found 20 (12%) of the monthly series to be inhomogeneous at the 99% significance level. These homogeneity tests, subsequently extended to the study period 2000–2010, represent an objective way to select data of sufficient quality for our computation of the solar absorption climatologies in Chapter 5.

Limitations & Outlook

- In general, it is recommended (Peterson et al. [1998]) to test the homogeneity of a timeseries relative to a neighboring timeseries that is supposedly homogeneous. If the two series are not sufficiently correlated, absolute tests as applied here, which use only the single station series, are considered more powerful than relative tests [Wijngaard et al., 2003]. The coverage by surface sites is quite dense over Europe, hence the relative testing could be an option. Over other continents, such as Africa or South America, the relative testing is impossible due to the rather poor spatial coverage by sites.

- Instead of omitting inhomogeneous timeseries as done here, homogenization [Sanchez-Lorenzo et al., 2013b] represents a way of correcting and maintaining the data for further
analysis. This, however, is not straightforward and requires expertise and time that lies beyond the scope of the present thesis.

- The single-change point tests identify only one inhomogeneity in a timeseries. To assess the full extent of temporal heterogeneity, as also needed for the homogenization of a series, the use of multiple-change point tests is inevitable, especially when working with longer-term timeseries [Sanchez-Lorenzo et al., 2013].

Chapters 3 and 4
Based on a satellite-derived SSR dataset of high horizontal resolution (0.03°), we quantified the spatial representativeness of 887 surface sites with respect to their larger surroundings of variable size and the fixed 1° grid, on which the TOA irradiances are provided that we use to derive atmospheric solar absorption (Chapters 5 and 6). The study is spatially constrained to Europe (Chapter 3) and the viewing field of the first generation Meteosat satellites (Chapter 4). On average, we found climatological (2000–2010) monthly and annual mean absolute representation errors of 1–3% (3–5 W m\(^{-2}\)) with respect to site-centered 1° surroundings and the fixed grid. In practice, we use the derived site-specific representation errors to adjust the spatial representativeness of the observational SSR records with respect to the gridded TOA product to eliminate potential collocation errors [Li and Trishchenko, 2001] in our absorption estimates computed in Chapters 5 and 6. Moreover, we studied the spatial subgrid variability in grids of 1° and 3° resolution and found that a dataset of coarser horizontal resolution, e.g., 0.25°, is likewise useful to derive this quantity. As we also showed that we can reliably approximate the site-specific representation errors from subgrid variability, a dataset of coarser resolution could potentially be used to estimate the representativeness of surface sites on the full global scale.

Limitations & Outlook
- The conclusions drawn strongly depend on the assumption that the high-resolution data capture the spatial variability in SSR realistically. We validated the spatial variability in all-sky SSR over Europe and more densely over the Swiss Central Plateau with satisfying results. However, in this dataset the variability in SSR is predominantly caused by clouds, the only parameter that effectively varies at the 0.03° resolution. Other retrieval input variables leading to spatial variability in SSR, such as surface properties, water vapor, and aerosol, are partially of coarser horizontal resolutions. Hence, altitude and aerosol effects under clear-sky conditions are likely underestimated. Certainly, once a new version of this dataset with improved treatment of these effects is available, the study should be repeated under both all- and clear-sky conditions.

- Another, not fully justified assumption concerns the question on whether the dataset’s spatial resolution of 0.03° is sufficiently representative of the point-scale, i.e., of the sky area as exposed to the radiometer at the surface. Working with SSR data of higher temporal resolution, e.g. daily or sub-daily, at which the representation errors are considered much larger [Li et al., 2005], the 0.03° resolution might still be too coarse. For the monthly and yearly temporal scales considered here, the 0.03° resolution is likely fine enough to be used as a surrogate for the point observations [Li et al., 2005]. From our analysis (Figure 4.4), we see that the average subgrid variability obtained from the 0.03° resolution data as compared to the point-resolution (intersect of extrapolation with y axis) might not be substantially underestimated. However, it is not clear whether the
study of point representativeness would suffer from larger biases. Testing this, requires
the use of either a finer resolved satellite product or a very dense network of ground
measurements to study the subgrid variability within the 0.03° grid itself (cf. Long and
Ackermann [1995]. Presently, both these options are not viable.

• The main drawback of the presented studies is their spatial limitation to the viewing
field of the Meteosat satellites. As we showed, a global satellite-based dataset of coarser
horizontal resolution, e.g. 0.25°, can potentially be used to approximate the spatial rep-
resentativeness of surface sites outside the Meteosat disk. With the missing site-specific
representation errors, the observational records could then not be adjusted, but at least
provided with a recommendation for their use in validation. Future work should certainly
make use of such a coarser global dataset and thereby assess the outcome in comparison
to the results obtained here.

• We showed that during the course of eleven years, the representation errors at 143 Euro-
pean sites do not significantly vary. Beyond that, we cannot exclude that a site’s repre-
sentativeness changes over time due to changes in climate regime, surface properties, or
urbanization effects [Alpert et al., 2005]. Considering different or longer time periods,
the results presented here might loose their absolute validity, which should be tested.

Chapter 5

In this Chapter, we provide solid estimates of the present day (2000–2010) mean-state solar ab-
sorption partitioning representative for Europe by combining ground-based SSR observations
with satellite-derived surface albedo and top-of-atmosphere net irradiance. Our best annual
mean estimates of solar absorption at the surface (ASRsurf) and in the atmosphere (ASRatm)
amount to 117.3 ± 6.1 W m⁻² (41.6 ± 1.6% of TOA irradiance) and 65.0 ± 3.4 W m⁻² (23.0
± 1.1%), respectively. The uncertainty in these estimates arises mainly from the measurement
accuracy of particularly the surface albedo and SSR data. The multiplicative combination of
the spatially averaged surface albedo and SSR data to obtain ASRsurf, as well as the spatial
representativeness of the SSR point observations, do not substantially enhance the uncertainty
range or could be corrected for, respectively. We see that seasonal and latitudinal variations in
the absorption estimates are more pronounced at the surface and in the total system than in the
atmosphere. Particularly the fractional ASRatm estimate at around 23% remains nearly con-
stant as a function of season and latitude. Therefore, we suggest this parameter to be suitable
for the first-order validation of climate models and satellite retrieval.

Limitations & Outlook

• To quantify reliable global mean estimates and to assess whether the fractional partition-
ing holds also for other regions of the Earth or even on a global scale, we might have to
use satellite-derived SSR data, since the coverage by surface sites is rather poor in many
continents of the world. Associated quality considerations may benefit from the quantita-
tive and qualitative insight gained here. Furthermore, we have completely neglected the
oceans and polar regions in our analyses, which poses a challenge in itself. Direct observ-
ations of SSR over the oceans exist to some degree in the form of buoys [e.g., Bourlès
et al., 2008], but require more elaborate quality control [Ingleby and Huddleston, 2007].

• A caveat of this study is the use of satellite-based surface albedo instead of direct mea-
surements taken at the ground. However, their limited availability and crucial issues con-
cerning their spatial representativeness [Roman et al., 2009], aggravate their application in our approach. A quite large number of different satellite-based surface albedo datasets exists [He et al., 2014]. Hence, a more elaborate sensitivity study using the different products might add to the understanding of uncertainty in our absorption estimates.

- Our estimates describe the absorption in the total atmospheric column. No information is provided on where in the atmosphere the absorption and corresponding heating occurs. To obtain vertical heating profiles, the analysis could be complemented by analyzing active remote sensor measurements, such as the CALIOP lidar system that provides high-resolution vertical profiles of aerosols and clouds [Winker et al., 2003, 2007], or upper air radiosonde measurements, providing vertical profiles of the up- and downwelling solar fluxes [Philipona et al., 2013]. Furthermore, radiative transfer models [e.g., Kim and Ramanathan, 2012] could be considered to study sensitivities and feedbacks related to vertical variations in atmospheric components, such as water vapor, aerosols, and clouds.

- In this thesis, we provide climatological estimates of surface and atmospheric absorption that represent the mean-state over the last decade (2000–2010). The study of interannual variations we neglected in most Chapters, except for Chapter 2, where we computed the trend tendency (2000-2007) in all-sky SSR over Europe based on 152 homogeneous timeseries. A future study should expand this analysis to the absorption estimates, which might exhibit different trend tendencies due to compensating or amplifying effects caused by temporal variations in surface albedo. For example, Zhang et al. [2010a] showed that the land surface albedo (MODIS) slightly decreased during 2000–2008 over Europe.

Chapter 6

In this Chapter, we quantify the cloud radiative effect on atmospheric solar absorption. We use continuous records of clear-sky SSR as derived at 22 surface sites worldwide and find that clouds enhance atmospheric absorption by around 11.5 Wm\(^{-2}\) (4%) in the climatological annual mean. By comparison, the positive cloud forcing as derived from the CERES EBAF satellite product is significantly smaller at 4 Wm\(^{-2}\) (1%) due to a strong overestimate in clear-sky atmospheric absorption. Within the frame of this product, the clear-sky atmospheric absorption is generally lower over the oceans as compared to the land, while the atmospheric cloud forcing is more pronounced, especially in the presence of low clouds. High clouds, on the other hand, exhibit a near-zero cloud radiative forcing on atmospheric solar absorption. Overall, the positive cloud effect on atmospheric absorption is more pronounced in the extra-tropics (low clouds) than in regions governed by the ITCZ (high clouds), which leads to a smoothing of the latitudinal distribution of atmospheric solar absorption under all-sky conditions.

Limitations & Outlook

- To explain the large discrepancy between the clear-sky SSR estimates as derived from direct surface measurements and as taken from the CERES EBAF satellite product, further testing of the employed algorithm [Long and Ackermann, 2000] is needed, as we cannot yet completely rule out inaccuracies in our approach and data processing. The implementation of the in-house archive to store and compute these fluxes from surface measurements has been successful and represents a firm basis for that.

- The spatial coverage by ground-based SSR measurements is relatively poor and regional averages representative for the global scale are not reliable. To obtain more robust es-
estimates and narrow down uncertainties on the global scale, particularly under clear-sky conditions and with respect to the cloud forcing, additional independent datasets should be considered and compared, such as the ISCCP-FD [Rossow and Zhang, 1995; Zhang et al., 1995] and GEWEX-SRB [Stackhouse et al., 2004] data products. Furthermore, climate models could help to better understand and disentangle feedbacks with respect to cloud type and other climatic variables.

**Concluding remarks**

With this thesis we demonstrated the potential of combining surface and satellite data to accurately determine the solar energy disposition over Europe and carefully discussed the sources and magnitude of associated uncertainties. We thereby relied on high-quality observations and put particular emphasis on the study of spatial-scale disparities that ensue from our methodology of combining point measurements with gridded satellite data. The assessment of point representativeness is a necessity in our application, but also in several others, such as the validation of climate models and the design of monitoring networks. The main limitation and option for future research concerns the assessment’s spatial extension to the full global scale.

Tools to derive the clear-sky surface solar radiation flux from worldwide in-situ measurements have been successfully implemented and allow to examine the impact of cloud radiative forcing on atmospheric solar absorption from the ground perspective. We find that clouds play a major role in maintaining the fairly uniform latitudinal distribution of fractional atmospheric solar absorption within the frame of a global satellite-based data product.

To obtain robust global estimates of atmospheric solar absorption under clear-sky and all-sky conditions, despite the poor coverage by surface sites, and to better understand the role of clouds in modulating the spatial patterns, we need to involve additional independent datasets originating from satellite retrieval. These should include solar radiation and surface albedo data, as well as cloud and aerosol properties, which may help to better constrain the global estimates and to attribute the horizontal and vertical variability in atmospheric solar absorption. Furthermore, global climate models should be involved to fully grasp the significance and impact of an accurate solar absorption partitioning on atmospheric dynamics and hydrology, and to evaluate the necessity and potential of tuning these models accordingly.

As we provide climatological monthly and annual mean estimates of surface and atmospheric absorption that represent the mean-state over the last decade, a major option for future research concerns the study of interannual variability and the review of periods before 2000. In view of the valuable insights gained, this work presents a solid foundation to further improve the knowledge on the solar absorption partitioning between the surface and the atmosphere, which is essential to advance the understanding and simulation of our climate system.

“See that ball of fire in the sky? That’s the sun. It goes by many names: Apollo’s lantern, day moon, old blazy. The important thing is, never to touch it.”

H. J. Simpson


Wulfmeyer et al., The Convective and Orographically-induced Precipitation Study (COPS): the scientific strategy, the field phase, and research highlights, *Quart. J. Meteor. Soc.*, 137, 3–30, 2011.


Acknowledgments

First of all, I would like to thank my supervisor Martin, who has been a great mentor and supporter of my carrier ever since 2008, when we first met. Working with you was an honor, and I very much enjoyed our adventures abroad and the scientific world you introduced me to. Thank you for being my Doktorvater and believing in me!

Many thanks to my co-supervisor Doris, who contributed fundamentally to the success and fun I had with my research. You have always been very motivating and supportive. The decision to start this PhD project was not hard to make, knowing that you would be there along the way. My expectations were not belied, as we became a great team and friends.

I thank Christoph not only for taking part in my PhD committee, but most of all for the supervision of my Master thesis that made me realize my passion for research, for the joy I felt as a teaching assistant of his course, and the Siedwurst on Mount Säntis after a strenuous hike.

I am very grateful to Gabriela for her co-supervision and for hosting me in Pasadena. The visit at NASA JPL, trip to Mount Wilson, stroll in Hollywood, and the culinary pleasures, I will never forget. You took part in the greatest “Ups” of my PhD studies.

Furthermore, I thank Jörg for agreeing to be my external examiner, the critical assessment of my work, and the friendly relationship that we built over the years.

Although Arturo left to Spain two years ago, he still shares his wisdom with me, makes a great motivational trainer, and is always ready for a hilarious story. Thank you for backing me up!

Many thanks to the BSRN and CM SAF communities for their great work, support, and outstanding workshops. I am especially grateful to Chuck, for supporting our work through the exchange of a zillion emails, data, and the visit in Zurich.

I thank my beloved buddies on the L-floor and beyond, for great times discussing, drinking, dancing, working out, and goofing around, but most of all for their friendship. L-floor rulez!

I dedicate this thesis to my parents, as they are always by my side no matter what. And to the man of my life, Lasse, for his support, patience, and unconditional love. You are my sun.

Maria Hakuba, November 2014