Toward using atmospheric carbon dioxide observations to estimate the biospheric carbon flux of the Swiss Plateau

Author(s):
Oney, Brian Johannes

Publication Date:
2016

Permanent Link:
https://doi.org/10.3929/ethz-a-010677958

Rights / License:
In Copyright - Non-Commercial Use Permitted
Toward using atmospheric carbon dioxide observations to estimate the biospheric carbon flux of the Swiss Plateau

A dissertation submitted to
ETH ZURICH

for the degree of
Doctor of Sciences

presented by
BRIAN JOHANNES ONEY
born November 9, 1984
citizen of USA

accepted on the recommendation of
Prof. Dr. Nicolas Gruber, examiner
Dr. Dominik Brunner, co-examiner
Dr. Christoph Gerbig, co-examiner

2016
## Contents

<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Abstract</strong></td>
<td></td>
<td>v</td>
</tr>
<tr>
<td><strong>Zusammenfassung</strong></td>
<td></td>
<td>vii</td>
</tr>
<tr>
<td><strong>1 Background</strong></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>1.1</td>
<td>“Bottom-up” carbon flux estimation</td>
<td>5</td>
</tr>
<tr>
<td>1.2</td>
<td>“Top-Down”, inverse carbon flux estimation</td>
<td>7</td>
</tr>
<tr>
<td>1.3</td>
<td>Regional-scale inverse carbon flux modeling</td>
<td>11</td>
</tr>
<tr>
<td>1.4</td>
<td>This work</td>
<td>17</td>
</tr>
<tr>
<td><strong>2 Atmospheric carbon measurements in the CarboCount CH Project</strong></td>
<td></td>
<td>19</td>
</tr>
<tr>
<td>2.1</td>
<td>Introduction</td>
<td>19</td>
</tr>
<tr>
<td>2.2</td>
<td>Reference gases</td>
<td>20</td>
</tr>
<tr>
<td>2.3</td>
<td>Measurement system at Lägern-Hochwacht</td>
<td>21</td>
</tr>
<tr>
<td>2.4</td>
<td>Measurement calibration and uncertainty</td>
<td>22</td>
</tr>
<tr>
<td>2.5</td>
<td>Ambient and reference gas measurements</td>
<td>31</td>
</tr>
<tr>
<td>2.6</td>
<td>Practical monitoring considerations</td>
<td>33</td>
</tr>
<tr>
<td>2.7</td>
<td>Conclusions</td>
<td>36</td>
</tr>
<tr>
<td><strong>3 The CarboCount CH sites: characterization of a dense greenhouse gas observation network</strong></td>
<td></td>
<td>39</td>
</tr>
<tr>
<td>3.1</td>
<td>Abstract</td>
<td>40</td>
</tr>
<tr>
<td>3.2</td>
<td>Introduction</td>
<td>40</td>
</tr>
<tr>
<td>3.3</td>
<td>Data and methods</td>
<td>42</td>
</tr>
<tr>
<td>3.4</td>
<td>Results and discussion</td>
<td>47</td>
</tr>
<tr>
<td><strong>4 A CO-based method to determine the regional biospheric signal in atmospheric CO₂</strong></td>
<td></td>
<td>61</td>
</tr>
<tr>
<td>4.1</td>
<td>Abstract</td>
<td>62</td>
</tr>
<tr>
<td>4.2</td>
<td>Introduction</td>
<td>62</td>
</tr>
<tr>
<td>4.3</td>
<td>CO₂ data analysis framework</td>
<td>64</td>
</tr>
<tr>
<td>4.4</td>
<td>Data and methods</td>
<td>65</td>
</tr>
<tr>
<td>4.5</td>
<td>Results &amp; discussion</td>
<td>71</td>
</tr>
<tr>
<td>4.6</td>
<td>Conclusions</td>
<td>85</td>
</tr>
<tr>
<td><strong>5 Synthesis and outlook</strong></td>
<td></td>
<td>87</td>
</tr>
<tr>
<td>5.1</td>
<td>Summary</td>
<td>87</td>
</tr>
<tr>
<td>5.2</td>
<td>Lessons learned</td>
<td>89</td>
</tr>
<tr>
<td>5.3</td>
<td>Outlook</td>
<td>90</td>
</tr>
<tr>
<td><strong>A Measurement data processing code</strong></td>
<td></td>
<td>95</td>
</tr>
<tr>
<td>A.1</td>
<td>Introduction</td>
<td>95</td>
</tr>
<tr>
<td>A.2</td>
<td>Data Processing and Management</td>
<td>96</td>
</tr>
</tbody>
</table>
Abstract

The lack of knowledge of the terrestrial carbon cycle translates into uncertain climate change projections due to the strong, yet uncertain relationship between terrestrial carbon fluxes and climate. Atmospheric carbon observations (defined here as the sum of CO$_2$, CH$_4$, and CO) integrate information on carbon fluxes on Earth’s surface, which can be used to assess the understanding of these processes through inverse carbon flux modeling. Due to the high spatial and temporal variability of terrestrial carbon fluxes, atmospheric observations representative of the regional scale (∼10–1000 km) are necessary to better understand these fluxes. My contributions have aided the goal of development of a comprehensive carbon observation and modeling system. This system aims to better quantify and understand natural fluxes and anthropogenic emissions over the Swiss Plateau, as part of the CarboCount project, using observations from its newly established network of four sites: Beromünster, Früebiel, Gimmiz, and Lägern-Hochwacht.

The accurate measurement of atmospheric carbon is a prerequisite of inverse carbon flux modeling. Therefore, reference gas cylinders were prepared, their mixing ratios referenced to the respective international scales, and distributed to the observation sites, in order to complete site construction. The simple measurement system at Lägern-Hochwacht has, except for a single pump failure and an extended failure to store data, successfully operated since August 2012 and delivered data sets with a temporal coverage of more than 97%. Therefore, a detailed description of its instrumentation is presented. The measurements of all four sites were repeatedly evaluated for quality with the reference gases. The uncertainty assessment of these measurements and their temporal aggregation are presented and discussed. Finally, gathered experience is offered for the future long-term, cost-effective monitoring efforts of atmospheric carbon.

The value of an atmospheric carbon monitoring site to regional-scale studies depends on the information contained in its observations. The seasonal and diurnal meteorological variability of the lower troposphere play an important role in determining this information. Therefore, the characteristics relevant to forthcoming regional scale modeling studies of the established observation sites were investigated, and strengths and weaknesses of the site’s data sets as well as the employed atmospheric transport models are discussed. Due to local topography, tower characteristics, and site elevation, among others, observations differ between sites, especially during nighttime. However, these observations differ much less during daytime, owing to intense daytime vertical mixing. From the analysis of simulated surface sensitivity, it is likely that atmospheric carbon observations consistently representative of the Swiss Plateau are provided by Beromünster and Lägern-Hochwacht. On the other hand, temporal filtering of the observations from Gimmiz and Früebiel is likely necessary to remove local influence, due likely to the model’s inability to accurately represent transport in the lower troposphere. Furthermore, due to the complex terrain directly surrounding Lägern-Hochwacht, similar filtering of its observations may be also necessary. These observations contain much information reflecting the complexity of the Swiss Plateau landscape, and will assuredly provide a challenge for future inverse modeling studies.

To constrain biospheric carbon fluxes with carbon dioxide CO$_2$ observations, it is necessary to first isolate the biospheric component of these observations. The standard procedure to accomplish this entails using an
atmospheric transport model to simulate the anthropogenic CO$_2$ component and the initial or background CO$_2$ mixing ratios. However, this introduces considerable uncertainty into the biospheric component and thereby the inverted biospheric carbon fluxes. With this in mind, a method to isolate the biospheric portion of CO$_2$ observations using carbon monoxide (CO) observations is developed, presented, and evaluated using observations from the Beromünster and Lägern-Hochwacht sites. Basically, this method scales CO observations above background CO mixing ratios to anthropogenic CO$_2$ using the observed wintertime CO$_2$/CO regional signal relationship. The evaluation suggests that the proposed method substantially improves our ability to determine the biospheric CO$_2$ signal. Performance of the method decreased when anomalously CO-enriched air masses were brought by northeasterly winds. Qualitative interpretation of the resulting biospheric signals confirms the expectation that the Swiss Plateau acted as a carbon sink during the major growing season of 2013 (May to August). Furthermore, the biospheric signals and related carbon fluxes are sensitive to solar radiation, precipitation, and ambient air temperature. Here, higher air temperatures (> 20°C) likely correlate with a diminished strength of the Swiss Plateau carbon sink.

This work not only contributed to the successful installation and operation of a new observation network, but also lays the foundations for future inverse carbon flux modeling studies. Accomplishments include: gaining invaluable observation site operation experience, demonstration of the rich information observed at the observation sites, indication which sites are suited to regional-scale carbon studies, and the development of a method to isolate the biospheric signal from CO$_2$ observations while circumventing problems of the standard approach. All of this sets the stage both for future observation endeavors and provides detailed insight for future carbon flux inversion work.
Zusammenfassung

Mangelndes Wissen über den terrestrischen Kohlenstoffkreislauf führt zu unsicheren Projektionen des Klimawandels aufgrund der starken, aber unsicheren Beziehung zwischen terrestrischen Kohlenstoffflüssen und dem Klima. Atmosphärische Kohlenstoffmessungen (hier die Summe von \( \text{CO}_2 \), \( \text{CH}_4 \), und \( \text{CO} \)) integrieren Informationen über Kohlenstoffflüsse auf der Erdoberfläche, die verwendet werden können, um das Verständnis dieser Prozesse zu beurteilen anhand inverser Modellierung der Kohlenstoffflüsse. Aufgrund der hohen räumlichen und zeitlichen Variabilität terrestrischer Kohlenstoffflüsse, sind \( \text{CO}_2 \)-Beobachtungen notwendig, die für regionalen Skalen (\( \sim 10–1000 \text{ km} \)) repräsentativ sind, um diese Flüsse besser zu verstehen. Diese im Rahmen des CarboCount Projekts durchgeführte Arbeit zielt darauf ab, das Verständnis der Kohlenstoffflüsse im Schweizer Mittelland mit Beobachtungen von vier neu etablierten Standorten zu erweitern: Beromünster, Früebüel, Gimmi und Lägern-Hochwacht.


Um biosphärische Kohlenstoffflüsse mit Kohlendioxidmessungen (\( \text{CO}_2 \)) zu bestimmen, ist es notwendig die

Zu den wichtigen Leistungen der Arbeit gehört die Sammlung von Betriebserfahrungen auf den Messstandorten, die von unenschätzbarem Wert sind, das Erstellen erster Datenanalysen, das Finden von Hinweisen darauf welche Beobachtungen geeignet sind um auf regionalen Skalen Kohlenstoffflussstudien durchzuführen, und die Entwicklung einer Methode zur Trennung des biosphärischen CO₂ Signals ohne Modell- und Inventarunsicherheiten zu übertragen. Alles in allem schafft dies eine fundierte Grundlage für künftige Messkampagnen und stellt einen guten Anknüpfungspunkt für nachfolgende Studien zu Kohlenstoffflussinversionen dar.
Chapter 1

Background

Atmospheric carbon consists mainly of carbon dioxide (CO$_2$) and methane (CH$_4$). Before the Industrial Revolution, their atmospheric mole fractions, in molar parts per million (ppm) of CO$_2$ and CH$_4$ varied from 180 to 280 ppm, and from 0.35 to 0.8 ppm during the last 800,000 years, respectively, along with glacial cycles and thereby global temperature [Petit et al., 1999; Siegenthaler et al., 2005; Loulergue et al., 2008; Lüthi et al., 2008]. With increasing technological progress, the Industrial Revolution began around 1750 AD, and the ability to harvest and consume natural resources increased vehemently. Coal and, later on, oil began to be harvested and burned at unprecedented rates, which caused the atmospheric mole fractions of CO$_2$ to increase. Growing scientific concern about the influence of increasing CO$_2$ mole fractions, a persistent greenhouse gas, on global temperature [Arrhenius, 1896; Callendar, 1949], eventually lead to the beginning of long-term monitoring in 1958 at Mauna Loa, Hawai‘i and at the South Pole, Antarctica [Keeling, 1960].

Since then, monitoring of CH$_4$, a more potent but less persistent greenhouse gas, was initiated in the early 1980s [Dlugokencky et al., 1998]. Towards the end of 2015, atmospheric mole fractions of CO$_2$ and CH$_4$ were approximately 400 ppm and 1.9 ppm, respectively.

During the period 2000-2010, observations indicate that 200 Pg (Pg: $10^{15}$ grams) of carbon flowed annually between the atmosphere and the Earth’s surface (Figure 1.1), mainly in the form of CO$_2$. During the seasonal cycle, land ecosystems breath in $\sim$123 Pg of carbon during the solar summer [Beer et al., 2010], which is used and respired shortly thereafter or stored as plant tissue, most of which dies and decomposes as solar winter begins. This behavior is highly dependent on weather and climate. The marine biosphere exhibits similar behavior, but has less amplitude ($\pm$80 PgC) and is highly dependent on ocean circulation and carbonate chemistry. Before the Industrial Revolution, these large, seasonal fluxes were smaller (Figure 1.1, black arrows) and roughly balanced each other in the course of a year. However, since then the carbon cycle has intensified with the increasing atmospheric carbon mole fractions, and accumulations or sinks of carbon in the ocean and land biosphere have also increased (Figure 1.1, red arrows).

Paleoclimatic studies indicate that the carbon cycle was tightly coupled with climate [Siegenthaler et al., 2005]. The scientific consensus about the current temperature anomaly is that CO$_2$ mole fractions are very likely driving climate [Stocker et al., 2013]. Therefore, to understand future climate change, we must understand the global carbon cycle. To this end, we must first understand and reproduce the unnatural or anthropogenic fluxes of CO$_2$ into the global carbon cycle from 1750 to now (until 2011; Figure 1.2). From historical statistics of fossil fuel use and cement production [Andres et al., 2012], and land-use change [Houghton et al., 2012], we can reconstruct past anthropogenic CO$_2$ emissions. From atmospheric mole fractions, we precisely know that 240±10 PgC has remained in the atmosphere. From profile observations of oceanic pCO$_2$ and inverse modeling, stable isotope ratios of CO$_2$ [Ciais et al., 1995], as well as from observations of atmospheric oxygen [Keeling et al., 1993; Battle et al., 2000], we have a confident estimate of –155±30 PgC that has been
absorbed by the ocean [Sabine et al., 2004; Khatiwala et al., 2013]. Because there is little scientific consensus about the directly determined flux of atmospheric, anthropogenic CO$_2$ into the natural land biosphere, after accounting for land use change (+180 ± 80 PgC), the magnitude of the land biospheric flux of $-160 ± 90$ PgC (1750–2011, from Table 6.1 in Ciais et al. 2013) is determined by subtracting atmospheric accumulation and oceanic anthropogenic carbon uptake from known anthropogenic emissions (Figure 1.2). The anthropogenic carbon flux into natural land ecosystems, or the terrestrial biosphere, exhibits two interesting features. First, interannual variability of this sink is large and appears to co-vary with climate, especially drought events [Ciais et al., 2005; Peters et al., 2007; Reichstein et al., 2007; Phillips et al., 2009]. Second, this sink appears to be increasing in magnitude [Ballantyne et al., 2012]. A major goal of understanding the carbon cycle is to answer the question whether this sink will continue to increase, or will climate change cause this sink to become a source.

Terrestrial carbon cycle dynamics are difficult to predict due to the complex relationships between weather and climate, and the numerous and diverse terrestrial ecosystems of the land biosphere [Heimann and Reichstein, 2008]. That is, general scientific consensus does not exist about the reaction of the land biosphere to rising
temperatures, rising CO$_2$ mole fractions i.e. the atmospheric fertilization effect [Prentice and Harrison, 2009], and a changing, and possibly intensifying hydrological cycle [Ciais et al., 2013]. The uncertainties in future climate projections are numerous, but the lack of consensus about the relationship between climate and the terrestrial carbon cycle is mainly responsible for the spread of future climate projections (Figure 1.3). This contrasts with consensus about the reaction of the ocean carbon cycle to these drivers. Therefore, terrestrial carbon cycle scientists are tasked with explaining this contemporary anthropogenic carbon flux into the land biosphere.

The carbon cycle is an immense and wondrous phenomenon of planet Earth, and the rest of this thesis chapter briefly introduces the range of accepted methods to determine the carbon flux from the land biosphere to the atmosphere. After partial review of the methods to determine the terrestrial carbon flux, the focus shifts to the study of regional-scale carbon fluxes and sets the stage for the scientific contributions of this thesis. This lack of review will hopefully be excused given the breadth and depth of scientific inquiry into the global carbon cycle up to this point in time, and given the scope of this thesis. For a comprehensive review of carbon cycle literature, please see the Intergovernmental Panel on Climate Change’s fifth synthesis report [Stocker et al., 2013], specifically Chapter 6 [Ciais et al., 2013]. For ongoing updates of the magnitudes of these fluxes please see Le Quéré et al. [2015].

Natural carbon fluxes at the land surface include vegetation photosynthesis and respiration where plants take in CO$_2$ through their stomata and, together with the sun’s rays and water, synthesize sugar, also
known as gross primary production (GPP), which is stored for later use or used shortly thereafter, and respired back to the atmosphere as CO$_2$, also known as autotrophic respiration (RA). Not all of this carbon is released back to the atmosphere within the lifetime of the plant. Plants concentrate carbon in the form of plant tissue, which can fall prey to herbivores or burn, also resulting in the release back to the atmosphere. Heterotrophic respiration (RH) describes the consumption or decomposition of organic matter by animals and microorganisms, mainly soil biota, and subsequent release to the atmosphere as CO$_2$. On longer timescales, the soil carbon, which is not metabolized and respired by the soil biota, is either retained and buried, or is washed into the oceans by rivers [Regnier et al., 2013; Le Quéré et al., 2015]. This natural cycle can also be disturbed by fire, insects, among other natural calamities.

Unnatural fluxes caused by human activity, henceforth anthropogenic, mainly include fossil fuel and cement production emissions, and emissions from land-use change. Fossil fuel emissions are determined using historical fuel consumption [Andres et al., 2012]. Land-use change carbon fluxes result from the initial land-use change and release of carbon, as well as from the following uptake of carbon of mainly crops or grasslands that replaced the original land cover [Houghton, 2003].

There are many approaches to determine the carbon fluxes over land. These tend to favor either extrapolation of small-scale (1–1000 m) observations to large-scale areas (Section 1.1), or partition global-scale observations
1.1 “Bottom-up” carbon flux estimation

A challenge of contemporary land carbon flux studies is to construct spatially and temporally accurate anthropogenic and biospheric flux inventories. Because it is unfeasible to exhaustively measure carbon fluxes at all land surfaces, one is forced to scale local observations up to larger areas. Therefore, assumptions need to be made about how fluxes behave elsewhere, which introduces an uncertainty of extrapolation.

1.1.1 Spatially explicit anthropogenic carbon fluxes

Total estimates of anthropogenic emissions are well-known from statistics of fuel consumption and cement production, although their uncertainty increases with their magnitude, as it has in recent decades [Ballantyne et al., 2015]. In an atmospheric transport modeling context, these emissions need to be spatially and temporally disaggregated, which is a formidable task. For example, annual national greenhouse gas emissions are reported to the United Nations Framework Convention on Climate Change (UNFCCC), and these can be disaggregated based on spatial population density or consumption, or a combination thereof, among others. Furthermore, seasonal variation of fuel consumption rates also needs to be taken into account, but vary between and within countries. Much work has gone into constructing consistent temporally and spatially resolved emission inventories, e.g. for the US [Gurney et al., 2009], Europe [Ciais et al., 2010a; Thiruchitrambalam, 2014], and the world [Olivier et al., 2005, 2011]. Nonetheless, these inventories have considerable uncertainties.

The land-use change flux since 1750 (180 ± 80 PgC) is the least certain of the anthropogenic fluxes. The bookkeeping approach [Houghton, 1999] compiles historical estimates of land-use change and applies a model of the net carbon flux caused by the initial land-use change (e.g. deforestation) and recovery or land-use. Land surface models and remote-sensing data (see below) have also been employed to improve estimates of the land-use change flux. The bookkeeping approach remains the preferred method, but all of three approaches are roughly consistent [Ciais et al., 2013].

1.1.2 Observations of the land biosphere

Relative to the anthropogenic fluxes, land biosphere fluxes are much less certain. This immense task has been approached from many perspectives, and include observations and simulations from:

1. Direct flux observations using eddy covariance methods,
2. Forest growth inventories, and

Direct surface carbon flux observations are derived from the correlation of simultaneous high-frequency measurements of CO₂ and the vertical wind speed [Baldocchi et al., 1988; Foken, 2008]. These observations have been carried out in the global long-term observation network called FluxNet [Baldocchi et al., 2001]. They have proven invaluable to investigate the response of the observed land cover type to climate, such as precipitation, temperature, and incoming solar radiation [e.g. Law et al., 2002], and have contributed much to understanding the terrestrial carbon cycle. These observations are however representative only of a local scale (< 1 km).
Inventories of timber and forest growth maintained by forest agencies around the world also record CO$_2$ uptake on longer time scales (> 10 years) as forest biomass. According to Pan et al. [2011] forests may account for the entire annual terrestrial carbon sink of approximately –2 PgC. Taking the vegetation pool from Figure 1.1 as 550 PgC, and the global forest carbon pool from Pan et al. [2011] approximately 80% of the vegetation carbon pool takes the form of a tree. Indeed, most of land-use change emissions can be attributed to deforestation [Houghton, 2003], which, since the beginning of the twentieth century, has occurred mainly in the tropics, as tropical countries have developed [Houghton, 2003].

Satellite imagery has enabled the long-term remote sensing of land surfaces since the launch of the first Landsat satellite in 1972. The extensive Landsat imagery has enabled the study of large-scale land cover change, most importantly for forest cover change [Hansen et al., 2013]. Long-term observations of seasonal variation in vegetation greenness have also been especially fruitful for recording large-scale vegetation dynamics [Stöckli and Vidale, 2004], especially in under-sampled regions [Anyamba and Tucker, 2005; Beck et al., 2006]. Recently, the ability to directly observe plant photosynthesis and thereby GPP with measurements of fluorescence has boosted understanding of short-term carbon cycle dynamics [Frankenberg et al., 2011, 2014]. Also, the LIDAR (light detection and ranging) retrievals of forest canopy structure allows assessment of the vertical structure and serve as a proxy for carbon stocks. This has recently been particularly useful for under-sampled tropical regions [Saatchi et al., 2011; Baccini et al., 2012]. Furthermore, synthetic aperture radar (SAR) can also directly map biomass and thus carbon stocks [Le Toan et al., 2011].

1.1.3 Integration and upscaling of land biosphere observations

Integration of the mentioned direct or indirect observations of natural carbon fluxes can take many forms. For example, remotely sensed data can provide detailed land cover maps, phenology, and indirect photosynthesis information to a land surface model [e.g. Stöckli et al., 2008]. Land surface models are important components of weather and climate models and have originally been developed to simulate the exchange of heat, momentum and water between the land and the atmosphere. As vegetation plays an important role in these exchange fluxes, the coverage and properties of vegetation need to be properly represented.

Simple land surface models used in numerical weather prediction attempt to capture the short-term variability of heat and water surface fluxes and are driven by short-term (< 30 days) weather, where vegetation distribution remains constant and disturbances are ignored [Noilhan and Planton, 1989]. They have also been used to calculate GPP and RA [Sellers et al., 1996; Mahadevan et al., 2008; Groenendijk et al., 2011]. Simplifying the land surface is a formidable task, and the range of complexity of these models is large, and largely reflects their application. More complex land surface models have been used to simulate past and future climates and therefore must account for vegetation change and variable climate forcings such as CO$_2$ as well as solar variability, depending on the time scale [Bonan et al., 2002b; Bonan and Levis, 2006]. To meet these primary goals on longer timescales, realistic representation of variables determining spatial vegetation distribution such as climate change, disturbances, the major biogeochemical cycles, especially those of nitrogen and carbon, must be taken into account [Ciais et al., 2013].

Eddy covariance measurement sites, although of local scale, sample the majority of the world’s biomes [Baldocchi et al., 2001], and offer valuable data sets to evaluate and constrain land surface models [Stöckli et al., 2008; Mahadevan et al., 2008]. Due to the global network, FluxNet observations can be directly scaled up based on observed relationships between climate and carbon fluxes. Jung et al. [2011] recently scaled eddy covariance measurements up to the global scale. Their estimate of CO$_2$ uptake is consistent with previous upscaled estimates [Beer et al., 2010], but total ecosystem respiration (heterotrophic and autotrophic combined) is biased low by approximately 5–10 PgC.

What about the respiration flux from larger animals? It seems that large (> 1 kg) animals likely would not
1.2. “Top-Down”, inverse carbon flux estimation

Contribute to heterotrophic respiration estimates based on eddy covariance measurements. Furthermore, the directly respired CO$_2$ from domesticated animals also does not appear to be included in emission inventories [Powers et al., 2014]. Given the large animal biomass of approximately 0.15 PgC [Smil, 2003], which eats approximately 3% of its body weight per day, assimilates approximately 20% thereof and expels the rest as CO$_2$ or soon-to-be-decomposed organic matter, we arrive at a very rough flux estimate of approximately 1.5 PgC yr$^{-1}$ ($0.15 \times 0.03 \times 365 \times 0.8$), which appears to not be accounted for. Within the context of the annual terrestrial carbon cycle variability (approximately $\pm 120$ PgC yr$^{-1}$ from Figure 1.1), this estimate appears to be negligible but would push typically underestimated annual total ecosystem respiration rates in the correct direction.

1.2 “Top-Down”, inverse carbon flux estimation

The basic tenet of inverse “top-down” surface carbon flux estimation is to determine carbon surface fluxes using observed atmospheric CO$_2$ mole fractions and an atmospheric transport model. The difficulty of modeling the observed variability of atmospheric carbon mole fractions lies in accounting for and adequately representing the various processes driving this variability. Observed mole fractions can be mainly attributed to four processes: upwind biospheric and anthropogenic surface fluxes, advected “background” mole fractions (beyond the short-term influence of surface fluxes), and atmospheric mixing. Of these processes, the biospheric surface fluxes and atmospheric mixing are the least well understood and therefore most difficult to predict. To better understand biospheric fluxes, observed atmospheric CO$_2$ mole fractions, spatially and temporally resolved surface flux inventories, and atmospheric models are necessary.

1.2.1 Atmospheric carbon dioxide observations

Charles Keeling and colleagues initiated long-term observations of CO$_2$ at Mount Mauna Loa, Hawai‘i and South Pole Antarctica in 1958 (Figure 1.4). After demonstration of large annual increases of atmospheric CO$_2$ mole fractions [Keeling, 1960], the US National Oceanic and Atmospheric Administration (NOAA) began to collect samples of CO$_2$ across the globe in the late 1960s [Komhyr et al., 1985]. These observations were taken at locations and times which were useful to determine the global mole fractions, in order to avoid the large variability resulting from local influence. As scientific interest shifted towards better understanding of the sources of smaller-scale variability, more observations were necessary.

Parallel to these observation efforts, technological advances also improved measurement capabilities. Initial long-term monitoring relied on flask samples for measurement in the laboratory of CO$_2$ mole fractions. Increasing electronic miniaturization and spectrometric advances allowed the construction of smaller, less expensive, field-deployable measurement devices. Generally, gas spectrometry relies on the Lambert-Beer law to determine light transmission through a gas sample. Techniques usually employ a light source emitting within a spectral region which is absorbed by the targeted gas species. Major advances include near infrared (http://www.licor.com/), fluorescence-based [Gerbig et al., 1996], and cavity ring-down spectrometers [Crosson, 2008], as well as integrated measurement systems [Stephens et al., 2011] which are, above all, field deployable. These autonomous, precise measurement devices have greatly eased atmospheric observation efforts.

In order to minimize the local influence, the first tall tower collecting atmospheric CO$_2$ observations was instrumented in North Carolina in June 1992 [Bakwin et al., 1995]. These observations were paramount to demonstrate the information content provided by observed, semi-continuous vertical CO$_2$ mole fraction profiles, leading to the instrumentation of a second tower in Wisconsin in October 1994 [Bakwin et al., 1998]. Later in 1992, the Energy Research Centre of the Netherlands supplemented the meteorological observation
Figure 1.4: CO₂ time series measured at Mauna Loa, Hawai‘i (MLO) and the South Pole Antarctica (SPO) by the Scripps Institute of Oceanography [Keeling et al., 2001].

tower near Cabauw, southwest of Utrecht, Netherlands, with CO₂ and CH₄ measurement devices [Vermeulen et al., 2011]. In 1994, a tall tower was instrumented with a CO₂ analyzer at Hegyhatsal, Hungary [Haszpra, 1995]. The expanding North American [Worthy et al., 2003; Andrews et al., 2014] and European [Vermeulen et al., 2004] tall tower observation networks have since greatly improved our ability to observe the land surface.

Ongoing efforts to constrain the terrestrial carbon flux, especially its interannual variability, have led to fruitful short-term research projects being maintained, extended, and upgraded to monitor more atmospheric species over longer periods of time. In Europe, the Integrated Carbon Observation System (ICOS) provides a framework for observation of carbon fluxes as well as atmospheric carbon mole fractions. It integrates existing carbon monitoring infrastructure and facilitates expansion of its network. On a similar note, the Integrated non-CO₂ Greenhouse gas Observing System (InGOS) focuses on CH₄, N₂O, SF₆ and halocarbons, and H₂. Together, these two infrastructure projects constitute an important effort to monitor the European greenhouse gas balance over climate-relevant time scales.

The Eurasian continent comprises Earth’s largest land surface, but the ecosystems within Russia and China are not as well sampled as those of Europe. In 2002, a Japanese-Russian collaboration instrumented the Berezhok tower in central Siberian Russia [Sasakawa et al., 2010; Saeki et al., 2013], and slowly expanded the Japan-Russia Siberian Tall Tower Inland Observation Network (JR-STATION). Outside the JR-STATION project, a German-Russian collaboration constructed and instrumented the Zottino Tall Tower Observatory (ZOTTO) by September 2006 [Kozlova and Manning, 2009], which was re-equipped in 2009 [Winderlich et al., 2010]. Additionally, the construction and instrumentation of a tower at Ambarchik in North Siberian Russia, bordering on the Arctic Ocean, was completed in 2014, further extending the continuous long-term
Asian greenhouse gas monitoring infrastructure (Reum, Goeckede, Heimann, pers. comm.). Unfortunately, few continuous greenhouse gas observations of equatorial regions exist. The Large Scale Biosphere-Atmosphere Experiment in Amazonia (LBA) intensively collected CO\textsubscript{2} and other trace gas observations at several Amazonian sites during 1999 [Andreae et al., 2002]. Although time-limited, this pilot study provided data suggesting a weak carbon sink of Amazonian land surfaces, which contradicted previous global inverse modeling studies. Numerous short-term airborne sampling campaigns have been carried out in the Amazonas [Gatti et al., 2014], but no continuous long-term greenhouse gas observations were made until the Amazon Tall Tower Observatory (ATTO) site began observations in 2012. The scientific community anxiously awaits the story the ATTO observations will tell [Wade, 2015].

The Global Atmosphere Watch (GAW) coordinates a global network of observation stations calibration and data quality centers, and world data centers. This important effort facilitates standardization of calibration procedures, and eases data exchange between experimentalists and modelers. To this end, The World Data Centre for Greenhouse Gases (WDCGG, http://gaw.kishou.go.jp/wdcgg/) under the GAW program collects and disseminates greenhouse gas observations. It is difficult to come by usage statistics, but GLOBALVIEW from NOAA appears to be the most cited data source for CO\textsubscript{2}.

### 1.2.2 Atmospheric transport modeling of CO\textsubscript{2}

Atmospheric CO\textsubscript{2} is usually treated as a passive tracer, and its mole fraction is thus simulated to be only influenced by surface fluxes [Keeling et al., 1989], thereby ignoring minute atmospheric sources. Atmospheric transport is commonly simulated in a Eulerian framework which discretizes space into a three-dimensional grid and transports CO\textsubscript{2} masses in space and time [Heimann and Keeling, 1989; Heimann, 1996; Heimann and Körner, 2003; Krol et al., 2005]. To simulate the CO\textsubscript{2} mole fraction time series at an observation site, one samples the CO\textsubscript{2} fields at the observation site position in the model.

Atmospheric transport can also be simulated in a Lagrangian framework. Lagrangian models can be run in backward mode (receptor-oriented i.e. simulating upwind surface influence of sites) tracking the movement and provenance of air parcels that would be observed at the observation site [Seibert and Frank, 2004]. The use of Lagrangian transport modeling for carbon flux studies is relatively new [Lin et al., 2003], especially the use of FLEXPART [Stohl et al., 2005]. Therefore, its description is warranted. The Lagrangian particle dispersion model (LPDM) FLEXPART, which simulates the transport and dispersion of air parcels (particles) via turbulent, advective, and convective processes, is driven offline by meteorological fields [Stohl et al., 2005]. In each simulation, \( N \) particles are released from the site’s position at site-dependent heights above ground corresponding to the targeted observation inlet’s position and tracked backwards in space and time over \( \Delta t \) or until they have left the simulation domain. The residence times \( \tau \) of air parcels near the surface describe sensitivity to surface fluxes.

These spatially gridded residence times within the simulation domain are computed as follows:

\[
\tau_{ik}(t, \Delta t) = \frac{\Delta t}{NK} \sum_{n=1}^{N} f_{ikn},
\]

where \( f \) is the binary switch of a single particle’s position in grid cell \( i \) at time \( k \), recorded \( K \) times during the simulation [Seibert and Frank, 2004; Stohl et al., 2005].

To simulate the dry air mole fraction \( \chi \) of the targeted chemical species, the residence times \( \tau \) (Eq. (1.2.1)) are scaled by the dry air density \( \rho \) (m\(^3\) kg\(^{-1}\)), multiplied with the mass surface flux (kg s\(^{-1}\) m\(^{-2}\); elements of \( x \) in Eq. (1.2.3)), and then converted into a volume flux by the sampling height \( h \) of particles, i.e. below 100 m air is assumed to be well-mixed and therefore influenced by surface fluxes. Molar mass factors \( M_{\text{air}} \)
Chapter 1. Background

and $M_{gas}$ then convert this into the desired mole fraction [Eq. (1.2.2) Seibert and Frank, 2004; Stohl et al., 2005].

$$\chi = \frac{M_{air}}{M_{gas} h} \sum_i \sum_k \tau_{ik}(h) \dot{q}_{ik} \rho_{ik}$$  \hspace{1cm} (1.2.2)

1.2.3 Bayesian flux inversion

In principle, atmospheric transport from land surfaces to an observation site can be simulated in a Eulerian or Lagrangian framework. To notate according to past inversion work, the transport equation (1.2.3) can be written as:

$$y = Hx \hspace{1cm} (1.2.3)$$

where $y$ is a vector of observations, $H$ is the transport model ("observation operator" in parlance) connecting the observation with the surface fluxes $x$ [Seibert and Frank, 2004]. In Equation (1.2.2), $\tau_{ik}$ operates linearly on the sources $\dot{q}_{ik}$, and would correspond to $H$ and $x$ in Equation (1.2.3), respectively.

Most carbon surface flux inversion studies often employ a Bayesian cost function (Eq. 1.2.4), which assumes Gaussian statistics and therefore employs a derivation of the equation of the normal distribution. The derivation typically aims to reconcile the differences between the simulated $Hx$ and the observed mole fraction $y$, while deviations of the state vector $x$ (the unknown parameters or quantities) from what is already “known” about the surface fluxes are penalized i.e. the differences between the unknowns $x$ are not allowed to substantially diverge from $x_{prior}$. Combined uncertainties of the observations and transport model ($C_{obs}^{-1}$), and prior fluxes ($C_{prior}^{-1}$) also influence the solution, but may have a subjective nature [Enting, 2002; Michalak et al., 2005]. That is, these covariance matrices can be used to further influence the solution.

$$J = \frac{1}{2}(y - Hx)^T C_{obs}^{-1} (y - Hx) + \frac{1}{2}(x - x_{prior})^T C_{prior}^{-1} (x - x_{prior}),$$  \hspace{1cm} (1.2.4)

There are many approaches to modifying and applying this equation, and the reader is referred to some relevant literature: Enting [2002]; Peters et al. [2005]; Bocquet [2008].

1.2.4 Previous modeling and flux inversion studies

Coarse, global, three-dimensional atmospheric transport models were initially used to infer surface fluxes of CO$_2$ from atmospheric CO$_2$ mole fraction observations [Keeling et al., 1989]. These carbon flux inversions coarsely discretized the land surface into continental regions [Bousquet et al., 1999]. The TransCom 3 model intercomparison experiments provided an important platform to compare both inversion methods and transport models [Gurney et al., 2002; Bakwin et al., 2004; Gurney et al., 2004], but the resulting inverted fluxes from these inversions were sometimes contradictory. Regardless of the same observations, same regions, and the same prior carbon flux, they found a large spread between inverted fluxes, which results mainly from the different transport schemes. Stephens et al. [2007] selected the results of those models which could best reproduce observed vertical CO$_2$ gradients, and hence transport, and the inverted carbon fluxes from this subset of models were roughly consistent. They indicated a weaker Northern hemispheric sink than previously thought. Further along, higher resolution models and the expanding CO$_2$ observation network were employed [Rödenbeck et al., 2003; Peters et al., 2007; Chevallier et al., 2010; Peters et al., 2010; Broquet et al., 2011].

The availability of a consistent, computationally affordable inversion method [Peters et al., 2005] as well as observations from the long-term tall tower network across the USA and Canada were the necessary ingredients for CarbonTracker [Peters et al., 2007]. This continental-scale (1,000–10,000 km) inversion is zoomed in on
1.3 Regional-scale inverse carbon flux modeling

North America at 1°×1°, and it estimates sets of weekly scaling factors of biosphere carbon fluxes, using an ensemble Kalman filter [Peters et al., 2005]. This method was then extended to focus on Europe [Peters et al., 2010], using the CHIOTTO network’s observations. Broquet et al. [2011] estimated summertime European fluxes at 0.5°×0.5°, and followed up with improved uncertainty estimates and evaluation metrics [Broquet et al., 2013]. They reported good simulation of seasonal CO$_2$ variability and thus fluxes, but the net annual flux remains uncertain. Therefore, long-term trends of the European biospheric fluxes cannot yet be determined reliably, and thereby their long-term reaction to climate also remains uncertain.

1.2.5 Challenges

Atmospheric transport model uncertainties are difficult to address. Sources of uncertainty specific to carbon flux inversion studies can be aggregation, representation, and rectification errors. The most common way to deal with these errors is to exclude or temporally smooth observations when the corresponding simulated CO$_2$ mole fractions are highly uncertain.

The representation error relates to the inherent mismatch between observed CO$_2$ variability and the true variability within the area of the overlying model grid cell [Gerbig et al., 2003a]. For example, local surface influence on observations from an area smaller than the grid cell’s area may dilute the information representative of a larger area i.e. the overlying model grid cell. This error tends to increase with the size of the overlying grid cell [Gerbig et al., 2003a; Tolk et al., 2008]. In global inversions, this problem was avoided by using temporally smoothed, extended data from background observation sites as in the GLOBALVIEW-CO$_2$ product [Masarie and Tans, 1995], which filters out this information. Another approach to this problem is to exclude locally influenced observations [Brooks et al., 2012].

The rectification error results from the temporal mismatch of vertical mixing and carbon flux dynamics [Denning et al., 1996; Lin and Gerbig, 2005]. For example, negative or CO$_2$ uptake fluxes correspond to a time of the year and the day when vertical mixing is greatest. On the other hand, positive or respiration fluxes at nighttime or during winter correspond to weak vertical mixing. If not captured in the atmospheric transport model, this temporal mismatch causes erroneous vertical distributions of CO$_2$ mole fractions. This is best diagnosed with comparison of the observed and simulated vertical profiles of CO$_2$ mole fractions, or observation of independent tracers such as radon [Schmidt et al., 1996].

The aggregation error results from the aggregation of spatial and temporal information of the carbon fluxes used in the inversion, by disregarding the spatial uncertainty of the aggregated fluxes in the inversion [Kaminski et al., 2001]. That is, it may result from the designation of a single biospheric land cover type for a region where more than one different land cover types exist. For example, a region of 100×100 km$^2$ has a total land cover that is 51% forest and 49% grassland, and the overlying grid cell would be assigned the predominant forest land cover type. Thereby, the observations would be driven by both forest and grassland fluxes, but the flux inversion would wholly lump it together with forest land cover types. Land surface models face a similar simplification error and Bonan et al. [2002a] offer a solution to represent a grid cell covering a collection of land cover types as fractional land cover types.

1.3 Regional-scale inverse carbon flux modeling

As introduced, bottom-up approaches suffer from the lack of representativity, and global top-down approaches suffer from aggregation errors. The regional scale allows resolution of these shortcomings by realistically representing the processes of bottom-up approaches while maintaining compliance with the global picture. Additional to the study of natural carbon flux variability, the regional scale can measure most administrative units, i.e. most administrative units have a horizontal dimension within 100–1,000 km. Therefore, regional-
scale carbon studies have the potential to appropriately verify national carbon emissions as reported to the UNFCCC.

Regional-scale carbon flux studies shift the focus from slow, smooth global variations of CO\(_2\) mole fractions to the rich information contained in relatively high frequency observations within the atmospheric boundary layer (ABL) above land surfaces. This large observed variability of atmospheric CO\(_2\) mole fractions is mainly driven by upwind anthropogenic emissions and biospheric CO\(_2\) fluxes. Ideally, upwind land surfaces within 1,000-10,000 km measurably affect mole fractions at the sampling location, whereas the local surface influence (< 10 km) is relatively weak.

This intermediate field of view resolves the heterogeneous spatial distribution of natural, agricultural, industrial, and residential land cover. Each of these land cover types has its own unique surface flux signature. Furthermore, natural land cover contains diverse ecosystems, which have different flux signatures, but also agriculture cultivates many different crops. Topography further adds to the spatial and temporal heterogeneity of carbon surface fluxes, due to its affect on meteorology. In order to understand this high spatial variability and resulting highly variable observations, high-resolution representation is necessary.

For inland regional-scale carbon flux modeling studies, a minimal atmospheric CO\(_2\) budget should consist of the regional anthropogenic (CO\(_2\),A) and biospheric (CO\(_2\),B) signals, as well as initial and boundary conditions (CO\(_2\),BG). It follows then that:

\[
\text{CO}_2 = \text{CO}_2,\text{BG} + \text{CO}_2,\text{B} + \text{CO}_2,\text{A}.
\]  

(1.3.1)

where the high variability and information content in the last two terms is represented in an atmospheric transport model, and spatially and temporally explicit surface flux inventories.

### 1.3.1 Regional-scale carbon flux inversion

Higher resolution lessens the discussed problems that plague coarse-scale carbon flux studies [Lin et al., 2003]. On the other hand, regional-scale modeling systems need to account for transport of CO\(_2\) from outside the domain and eventually for recirculation of CO\(_2\) tracers back into the region of interest [Roelenbeck et al., 2009; Rigby et al., 2011]. Especially, small uncertainties here can strongly influence the determination of carbon fluxes within the region of interest [Goeckede et al., 2010a].

Higher spatial resolution has the potential to reduce the representation error by accounting for the spatial heterogeneity and complex topography that may surround an observation site [Gerbig et al., 2003a; Tolk et al., 2008]. The validity of the assumption that a site’s observations are representative of an overlying grid cell depends on the observation site characteristics [surroundings, sampling height, etc. Tolk et al., 2008]. Here, a grid cell should be no bigger than \(30\times30\) km\(^2\) [Gerbig et al., 2003a], and ideally less than 10 km. To some degree, representation error will remain because of the balance struck between the need to mimic reality and computational capabilities. Nonetheless, a receptor-oriented Lagrangian transport framework such as STILT and FLEXPART allows flexible determination of the output grid and can therefore significantly reduce this uncertainty.

Arguably the most important contributor to the rectification error [Denning et al., 1996; Ahmadov et al., 2007; van der Molen and Dolman, 2007] and thus transport uncertainty in general is mesoscale topography-induced air flow. Because the “world is not flat”, i.e., because most of the world can be considered complex terrain [Rotach et al., 2014], the influence of topography generally alters airflow and also affects regional climate. This can be remedied in regional-scale modeling by moving to a spatial resolution which is sufficiently fine for the study region.

Higher spatial resolution also enables the underlying biophysical processes or the fluxes to be explicitly estimated in an inverse modeling framework without making a gross aggregation error (Figure 1.6). In a
parameter inversion, the inversion solves for the optimal set of biosphere parameters that yield the most probable flux [Raguen et al., 2005; Scholze et al., 2007; Tolk et al., 2011; Meesters et al., 2012]. Here, the inversion directly constrains the response of the biosphere to weather and climate. However, the observed variability contains only information about upwind land surfaces. A form of aggregation error is therefore made, in that it is assumed that the spatial variation within a certain land cover type is negligible, which has been shown to be questionable [Groenendijk et al., 2011]. Therefore, this pre-constraint must have good reasoning. As outlined by Tolk et al. [2011], nonlinear relationships within the biosphere model require advanced inversion techniques, such as an ensemble Kalman filter. Also, to avoid so-called aliasing effects, where the wrong parameter is corrected, one must be confident that the parameters in question are properly constrained [Tolk et al., 2011]. Additionally, the direct comparison of high-resolution biospheric flux simulations with directly measured surface fluxes is a possible evaluation tool [Ahmadov et al., 2007; Broquet et al., 2011; Tolk et al., 2011; Meesters et al., 2012].

A pixel inversion solves for the most probable flux or associated scaling factor of the flux within a land cover type [Figure 1.6 Tolk et al., 2011; Meesters et al., 2012]. It is thereby less rigid than the parameter inversion method, because it typically makes fewer presumptions about the relationship between biospheric flux variability and climate. To reduce the issue of too many under-constrained pixels (and correspondingly too many degrees of freedom), a spatial correlation between fluxes of the same land cover type within a certain spatial distance of each other is introduced to the prior covariance matrix \( C^{-1}_{\text{prior}} \). Here, the correlation length scale needs to be well justified, and the land cover data needs to be accurate [Tolk et al., 2011].

### 1.3.2 Previous regional-scale work

The CO\(_2\) budget and rectification airborne study (COBRA) during August 2000 intensively sampled the continental biospheric CO\(_2\) signals from the North American continent, by collecting vertical, continuous profiles of CO\(_2\) and CO [Gerbig et al., 2003a]. Concurring with the conclusions of Bakwin et al. [1995], they found most of the information of the continental surface fluxes to be within the ABL, whereas free tropospheric CO\(_2\) variability was low (Figure 1.5). Furthermore, they found that the maximum spatial increment allowable to resolve the information contained in the observations within the lower ABL is approximately \( \sim 30 \text{ km} \). Further COBRA studies have also contributed much to regional-scale carbon flux modeling [Lin et al., 2006; Matross et al., 2006].

With higher intensity, the CarboEurope Regional Experiment Strategy project supplemented a dense surface flux observation network in southwestern France with tall tower mole fraction observations and a short aircraft measurement campaign [Dolman et al., 2006]. These observations have been instrumental in guiding further European measurement campaigns. This campaign has proven especially fruitful to evaluate and develop transport and surface flux modeling strategies, including model development [Ahmadov et al., 2007], model intercomparison [Ahmadov et al., 2009], investigation of the rectification error [Ahmadov et al., 2007], and representation errors [Tolk et al., 2008], as well as the development of inverse regional modeling frameworks [Lauvaux et al., 2008, 2009a, b]. However, for annual studies, long-term atmospheric monitoring is necessary.

The US-American tall tower network was augmented with several tall towers in the upper Midwest in order to over-sample the potentially large carbon fluxes from maize [Miles et al., 2012]. Previous research had indicated a large carbon sink in the Northern hemisphere’s land [Garney et al., 2004] and in particular the potential carbon sink of maize [Suyker et al., 2005; Verma et al., 2005], which is cultivated in the upper Midwest USA—so much that it is known as the “corn belt”. Therefore, as part of the Mid-continental intense measurement campaign with the objective to sample an agricultural area \( 500 \times 800 \text{ km}^2 \), the construction of an unprecedentedly dense network of greenhouse gas observation tall towers was initiated in 2006, and was augmented with an airborne measurement campaign during the summer of 2007. These observations have
Chapter 1. Background

Figure 1.5: Vertical, zonal profiles of CO$_2$ observations from a Maine to North Dakota and c from Idaho to Maine, USA, taken during the COBRA-2000 intense measurement campaign. From Gerbig et al. [2003a]

also served as an intense testing bed for modeling studies. Corbin et al. [2010] demonstrated the necessity to explicitly include crop fluxes, especially those of maize, in surface flux modeling studies. Schuh et al. [2013] further demonstrated the necessity of high-resolution modeling in order to reproduce the spatial flux patterns in an inverse modeling framework. Ogle et al. [2015] demonstrated the limits and possibilities of using inverse flux modeling to verify national biospheric carbon budgets. Results from observed between-site CO$_2$ gradients [Miles et al., 2012] and site-exclusion inverse modeling tests [Lauvaux et al., 2012b] suggest that footprint modeling and surface flux characteristics of the target region should guide regional-scale observation network design.

The Dutch CHIOTTO tower Cabauw and the long-established, coastal tall tower Lutjewad were supplemented with two rural tall towers, Loobos and Hengelman, for the year of 2008. Twice-weekly aircraft flux observations were also made during this period in order to evaluate inverted fluxes. The theoretical inversion
work of Tolk et al. [2011] laid the necessary foundation for the following work of Meesters et al. [2012], who applied and compared a pixel-based and parameter-based inversion method to constrain surface fluxes over the Netherlands (Figure 1.6). Their work identified some of the important pitfalls of inverse flux modeling. First, poor representation of nocturnal mixing may be related to an aliasing effect within the parameter inversion, which results in the prediction of negative respiration fluxes. Second, seasonal sets of parameters may be necessary to reduce the rigidity of a parameter inversion. Third, a separate land cover type dedicated
solely to maize is likely necessary.

Several studies have augmented existing tower observations with aircraft campaigns [Matross et al., 2006; Pillai et al., 2011], or equipping FluxNet sites with calibrated CO$_2$ measurement devices [Goëckede et al., 2010b], the latter being more useful for budgeting studies, due to the high temporal coverage. Goëckede et al. [2010b] and Pillai et al. [2011] were some of the first studies to demonstrate the value of high-resolution transport simulations above complex terrain.

### 1.3.3 Challenges for regional-scale carbon flux studies

The most important aspect of trace gas mole fraction modeling is the ability to simulate the movement of air parcels, and thereby the transport of their constituents. Driven by both advances in meteorological simulation and computational capabilities, the increase in spatial resolution of transport models to less than 30 kilometers allowed the more realistic representation of advection and convection as well as turbulence.

Lin et al. [2006] laid out the problems presented by the information-rich data sets representative of regional-scale areas. A summary of these and additional issues in regional-scale carbon flux modeling mainly includes transport model aspects, namely:

1. Accurate modeling of horizontal and vertical mixing is necessary to reproduce steep observed mole fraction vertical gradients (Figure 1.5).
2. Accounting for mesoscale topography induced airflow is necessary.
3. Mass conservation of transported tracers is absolutely necessary. Here, off-line transport models are especially sensitive to this issue.
4. The variable response of diverse ecosystems to weather is resolved at this scale and therefore requires realistic representation.
5. Sources of uncertainty require detailed analysis and inclusion in a flux inversion.
6. Limited-area modeling requires both accurate determination of “background” mole fractions and accounting for possible reentry of CO$_2$ masses originating within the area of interest.

Much work has been done to solve these problems as the field of regional carbon flux modeling has advanced. Improving spatial resolution appears to be the most endeavor. Although the field is inherently interdisciplinary, a great deal of progress can be seen.

Radon is a radioactive noble gas with a half-life of 3.82 days which is emitted mainly from soil, and spatially explicit radon emission inventories for modeling exist [Szegvary et al., 2007; Karstens et al., 2015]. Its use to correct for model transport uncertainties is established [Zahorowski et al., 2004; Hirsch, 2007], and new applications and refinements are continually being added [van der Laan et al., 2014]. Gamnitzer et al. [2006] provide an example of correcting the modeled regional fossil fuel signal by folding the simultaneous ratios of observed and modeled radon.

With the potential uncertainty contribution of about 30% to modeled CO$_2$ mole fractions [Gerbig et al., 2008], capturing vertical exchange of CO$_2$ within the ABL is a prerequisite for accurate quantification of surface carbon fluxes. The field of numerical weather prediction aims primarily at accurate prediction of temperature, wind, and precipitation. This may explain why vertical mixing tends to be poorly represented across models [Brunner et al., 2015], as indicated by the ability to predict the height of the ABL. Brunner et al. [2015] found that vertical mixing was overestimated in an ensemble of regional-scale models, especially in winter, which they evaluated at an airport in Canada and in Europe. Kretschmer et al. [2014] present an approach to
improve vertical mixing representation by geostatistical interpolation of observed ABL heights (radiosonde) to the model grid. This assignment of ABL heights had a positive effect on the simulation performance of CO$_2$ mole fractions and is a pragmatic step forward in reducing transport uncertainty. Nonetheless, improved simulation of vertical mixing would be the optimal solution.

1.4 This work

1.4.1 The CarboCount CH Project

The combination of top-down and bottom-up methods at a resolution that can resolve apparent variability of biospheric carbon fluxes is arguably the best way towards understanding terrestrial carbon fluxes. With this in mind, the CarboCount CH project aims to develop and implement a prototype atmospheric monitoring network and carbon flux modeling framework for CO$_2$ and CH$_4$ for Switzerland. At its core is a dense network of tower observation sites, and the fusion of the resulting observations with atmospheric transport models and highly detailed anthropogenic and biospheric flux inventories. The CarboCount CH observation sites possess diverse orographic characteristics that provide for challenging meteorological transport modeling, which warrants high-resolution atmospheric transport modeling. Furthermore, the strengths and weaknesses of each particular site need investigation to guide future observation networks. Eddy-covariance measurements from Swiss FluxNet can be used to evaluate the inverted regional-scale carbon fluxes. Furthermore, the inverted fluxes can be used to compare with a comprehensive land surface model of the carbon and nitrogen cycle, also developed within the project. Finally, results from this study could be integral in the development of a national greenhouse gas verification system.

1.4.2 My role

My work encompasses the two major components of top-down surface carbon flux determination: atmospheric CO$_2$ mole fraction observations and their simulation. My goal is to lay the foundations for subsequent work to constrain a biospheric CO$_2$ flux inventory using an atmospheric transport model and CO$_2$ observations.

My goals as an integral part of the CarboCount CH Project include:

1. Successful construction and maintenance of an atmospheric carbon monitoring site,
2. Understand what is driving the variability observed at this and the other CarboCount network observation sites,
3. Simulation of this observed variability using high-resolution atmospheric transport modeling of anthropogenic and biospheric carbon fluxes across the Swiss Plateau using FLEXPART-COSMO,
4. Investigation of the strong relationship between CO and CO$_2$ observed at the network’s sites.

However, the prerequisites for meaningful inversion of carbon surface fluxes over the Swiss Plateau are numerous. This preliminary work includes:

1. filling and calibration of reference gas bottles, and observation network deployment,
2. collection and processing of high-quality atmospheric carbon observations,
3. determination of which observations are representative of the regional scale,
4. assessment of possible atmospheric model transport uncertainties,
Chapter 1. Background

Figure 1.7: Schematic representation of the fundamental CarboCount CH project elements: tower observations, carbon fluxes (bidirectional arrows), and transport models (unidirectional arrows). Figure kindly provided by the Graphics Department, Empa.

5. investigation of the target region’s characteristics,

6. preparation of anthropogenic and biospheric flux inventories, as well as collection of background CO$_2$ fields,

7. tracer transport modeling and mole fraction simulation at all observation sites.

To reach these goals, with much help from colleagues, I have designed, constructed, and installed a measurement system at Lägern-Hochwacht, which was mostly duplicated at Früebüel. Detailed description of this instrumentation is presented in Chapter 2. Furthermore, I detail the processing, calibration, temporal aggregation, and uncertainty estimation of the atmospheric carbon observations from these and the two remaining CarboCount sites, Beromünster and Gimmiz. Finally, the experience gained through the operation of the Früebüel and Lägern-Hochwacht observation sites is discussed and offered to future monitoring efforts.

In Chapter 3, the observation site characteristics relevant to forthcoming regional-scale modeling studies are investigated. This is accomplished by comparing the observed meteorology and the meteorological model which drives FLEXPART-COSMO in this study, COSMO-2. Assessing the upwind surface influence on each observation site using FLEXPART-COSMO in light of the observed regional signals uncovers what is driving the observed variability. Finally, the strengths and weaknesses of the site’s observations as well as the employed atmospheric transport models are discussed. These results will hopefully guide and aid subsequent network deployments aimed at inverse carbon flux modeling studies of the Swiss Plateau.

In Chapter 4, a method to isolate the biospheric portion of CO$_2$ observations using CO observations is applied to Beromünster and Lägern-Hochwacht observations. The isolation of the biospheric signal from observed CO$_2$ mole fractions requires the subtraction of both background and anthropogenic signals, which, in the standard approach, requires estimation of these components with an atmospheric transport model, and background fields and anthropogenic emission inventories. This standard approach inevitably introduces uncertainty into the “observed” biospheric signal, which translate into the inverted biospheric flux inventories. Here, we propose a CO-based method to provide better estimates of the observed biospheric signal.
Chapter 2

Atmospheric carbon measurements in the CarboCount CH Project

2.1 Introduction

Regulating greenhouse gas emissions is necessary to curb rising atmospheric greenhouse gas mole fractions in order to avoid dangerous climate change [Stocker et al., 2013]. To this end, atmospheric carbon measurements representative of administrative regions are of particular importance to regulating anthropogenic carbon emissions [Ciais et al., 2014]. The monitoring and resulting regulation of carbon emissions should be supplemented with inverse carbon flux modeling using high-quality atmospheric carbon measurements containing information about the administrative region of interest [Ciais et al., 2014].

With the aim to quantify carbon fluxes and thereby the Swiss carbon budget, the measurement sites of the CarboCount CH network strategically spread across the Swiss Plateau (Table 2.1). The Beromünster site has a 217 m tall tower and is on a gentle hill 30 km southeast of Bern. The Früebüel site is an eddy covariance measurement site [Zeeman et al., 2010] located on Zugerberg ~10 km south of the city of Zug. The Gimmiz site has a small water tower in a relatively flat area ~2 km northwest of Aarberg in the Seeland region. The Lägern-Hochwacht site has a small tower atop the steeply sloped mountain ridge ~20 km north-northwest of Zurich. The strengths and weaknesses of each site’s characteristics and observations relevant to regional-scale carbon flux modeling are assessed in Chapter 3.

We have equipped the sites with PICARRO cavity ring-down spectrometers [Crosson, 2008] due to their relatively low cost, and reputation of being low maintenance and providing highly precise measurements [Richardson et al., 2012]. Although PICARRO measurement devices have been shown to measure greenhouse gases precisely and stably in the field [Richardson et al., 2012; Andrews et al., 2014], their absolute measurements drift slightly on time-scales of hours, days, weeks, and months depending on the trace gas species. Therefore, similar to other measurement techniques, these devices require repeated calibration during field deployment relative to an accepted international scale, in order to be able to compare with other measurements made elsewhere.

This chapter partly documents the methodologies and experience gained from atmospheric carbon measurements at the CarboCount sites. It describes the measurement system in place at Lägern-Hochwacht, and thereby to a large degree that in place at Früebüel. The intricacies of the complex, multiple-height measurement system at Beromünster are described by Berhanu et al. [2016], and thereby to a lesser degree that in place at Gimmiz. Furthermore, this chapter documents the aggregation, calibration, and uncertainty estimates of the network’s measurements. It also offers practical experience and suggestions regarding the
Table 2.1: Location and instrumentation of the measurement sites of the SNF Sinergia CarboCount CH Project.

<table>
<thead>
<tr>
<th>Site</th>
<th>Height(s) (m.a.g.l.)</th>
<th>Alt.</th>
<th>Lat., Lon.</th>
<th>Device</th>
<th>Serial</th>
<th>Gases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beromünster</td>
<td>212, 132, 72, 45, 12</td>
<td>797</td>
<td>47.1896, 8.1755</td>
<td>PICARRO G2401</td>
<td>CFKADS2038</td>
<td>CO₂, CH₄, CO, H₂O, CH₄, CO, H₂O</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>PICARRO G2311-f</td>
<td>CFHADS2018</td>
<td>CO₂, CH₄, H₂O</td>
</tr>
<tr>
<td>Fruebuel</td>
<td>4</td>
<td>982</td>
<td>47.1158, 8.5378</td>
<td>PICARRO G2301</td>
<td>CFADS2256</td>
<td>CO₂, CH₄, H₂O</td>
</tr>
<tr>
<td>Gimmiz</td>
<td>32</td>
<td>443</td>
<td>47.0536, 7.2480</td>
<td>PICARRO G2301</td>
<td>CFADS2255</td>
<td>CO₂, CH₄, H₂O</td>
</tr>
<tr>
<td>Lägernhöchwart</td>
<td>32, 23</td>
<td>840</td>
<td>47.4822, 8.3973</td>
<td>HORIBA APMA 360</td>
<td>207006 &amp; 306002</td>
<td>CO₂, CH₄, CO (H₂O)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>PICARRO G2401</td>
<td>CFKADS2043</td>
<td>CO₂, CH₄, CO, H₂O</td>
</tr>
</tbody>
</table>

elements of this chain of measurement activities, which link up to provide high-quality observations for inverse carbon flux modeling.

2.2 Reference gases

Ambient atmospheric carbon mole fractions can exhibit high variability depending on the measurement site’s location. Large variability is expected in the Northern Hemisphere (Figure 1.4), especially above land surfaces such as the Swiss Plateau. The accuracy of employed measurement devices within this range needs to be investigated. The range of mixing ratios of the reference gas bottles were therefore prepared in order to cover the expected range of ambient atmospheric carbon mole fractions. Specifically, this allows assessment of the accuracy of the measurement devices along the continuum of observed mole fractions.

Table 2.2: Approximate reference gas mole fractions of aluminum bottles. Mole fractions have units of \(\mu\text{mol mol}^{-1}\) mole fraction or molar parts per million (ppm).

<table>
<thead>
<tr>
<th>Gas Bottle</th>
<th>CO₂</th>
<th>CH₄</th>
<th>CO</th>
<th>No. of Bottles</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>470</td>
<td>2.4</td>
<td>0.24 or 1.4</td>
<td>7</td>
</tr>
<tr>
<td>Low</td>
<td>380</td>
<td>1.9</td>
<td>0.15</td>
<td>6</td>
</tr>
<tr>
<td>Working</td>
<td>400</td>
<td>2.1</td>
<td>0.20</td>
<td>5</td>
</tr>
<tr>
<td>Target</td>
<td>400</td>
<td>2.1</td>
<td>0.20</td>
<td>3</td>
</tr>
</tbody>
</table>

To this end, 30 L aluminum bottles were filled to their capacity of 2015 psi for the CarboCount CH project, with “high”, “low”, and “target” mole fractions (Table 2.2). They were filled with ambient air using a modified scuba diving pump at Empa Dübendorf, Switzerland, and dried in between the pump and the bottles with magnesium perchlorate to minimize water vapor and its effects in the aluminum cylinders. Therefore, the bottles shown in Table 2.2 have mole fractions below approximately 100 molar parts per million (ppm) H₂O. Additionally, the very high CO mole fractions among the high bottles were prepared for the HORIBA CO measurement device in place at Gimmiz. The bottle’s atmospheric carbon mole fractions were determined relative to the gas-specific international reference scales (CO₂: WMO X2007, Zhao and Tans 2006; CH₄: WMO X2004, Dlugokencky et al. 2005; CO: WMO CO X2014, Novelli et al. 1991). This was repeated several times for months after having filled the cylinders, to check for mole fractions to stabilize as well as to ensure accuracy of the mole fraction measurements. We report uncertainties of these child reference gases \(\sigma_{st}\) to approximately be (ppm) CO₂: 0.12, CH₄: 0.0003, and CO: 0.001. Afterwards, the reference gas bottles
2.3 Measurement system at Lägern-Hochwacht

2.3.1 General setting

Ambient air samples at Lägern-Hochwacht are collected at the top of a tower managed by SkyGuide LLC at a height of 872 meters asl, or 32 meters above ground level (agl), which corresponds to about 10 meters above the surrounding tree canopy. It is possible to sample a second inlet at approximately tree height (23.5 agl). The site has been equipped with a Picarro G2401 cavity ring-down spectrometer [Crosson, 2008] measurement device, measuring dry air mole fractions of CO$_2$, CH$_4$, CO, and H$_2$O trace gases. The measurement system is housed in the building at the base of the tower on a standard rack ($48.3 \times 59.7 \times 198.1$ cm), which is electrically grounded. The measurement room’s temperature is not regulated and varies from approximately 10 to 25$^\circ$C in winter and summer, respectively. Therefore, during the colder months, the bottom half of the rack is encased in 6-cm-thick Styrofoam padding, which raises the local temperature near the electrical instruments to approximately 20 degrees Celsius, which is the recommended operating temperature. Component details are listed in Table 2.3, and the corresponding schematic is shown in Figure 2.1.

2.3.2 Gas flow

Ambient air is suctioned through a fine paper filter inside the inlet housing down through a 40-meter-long, single piece of 12mm (OD) Synflex tubing at 101 min$^{-1}$ for approximately 13 s (Figure 2.1 and Table 2.3). It then flows through a one meter snippet of 1/2” Teflon tubing into the valve box, where it then flows through 1/4” Synflex tubing. The airstream then splits at the first tee-junction, to pass through the flow meter (FM1 or FM2), and on through the remaining 1/4” Synflex tubing to the purge pump (P1). For measurement, air can flow from this junction at approximately 0.205 l min$^{-1}$ for about 4 s through $< 1$ m of 1/4” Synflex, two 3-way solenoid valves (V1 & V2), a 7 µm filter to the measurement device’s measurement cavity, and through reinforced plastic tubing to the device pump (P2). Total residence time of ambient air samples in the tubing is approximately 18 s.

Sampling of the reference gases is carried out by simultaneously switching the second valve (V2) and one of the valves V3-V6. Brass three-stage pressure regulators maintain a constant, low overpressure ($\sim 10$-15 psi above ambient) on valves (V3-V6), which suffices to supply enough air to the measurement device. Reference gas then flows serially through the valves and through a mass flow controller at 0.211 min$^{-1}$. This serial airflow flushes any remnant reference gas or ambient air which has diffused in through the overflow. For example, upon switching on valve V2 and V3, air flows from the reference gas bottle through 1/16” stainless steel tubing, valve V3, and the mass flow controller (MFC). After this, reference gas can either flow through valve V2, through 1/4” Synflex tubing and into the measurement device, or through the overflow into the measurement room.

Valves are powered by the PICARRO and are only switched to sample reference gases or to sample the lower height. Should the valve box fail, standard measurement setting is to sample the top inlet. This setting assures that little strain is placed on the instruments and that energy use is minimal. It also assures that little or no risk exists of reference gas being lost due to a power outage. The mass flow controller is constantly open and could be used to detect internal valve leaks.

After a valve transition, the air sampled is a mixture of the previous and current gases, which invalidates the measurement. The amount of time necessary for equilibration was determined with reference gas measure-
ments to be 9 min for Lägern-Hochwacht and Früebüel. Due to these relatively long equilibration times of approximately 9 minutes and the relatively small vertical distance between the two inlets at Lägern-Hochwacht, the lower inlet was never sampled.

2.4 Measurement calibration and uncertainty

In general, measurements of a fundamental quantity such as light, electrical current, time, and/or mass are taken and these measured signals $s_{\text{meas}}$ are related to the desired quantity. The PICARRO instruments used in the network report measured signals as mole fractions by applying internal calibration factors, but these still need to be translated into mole fractions relative to the respective international scales. For the PICARRO devices, concurring with Rella et al. [2013], we have observed a linear relationship between known mixing ratios and measured signals and therefore employ Equation (2.4.1). Here, reference gas cylinders supply gas of known mole fraction at regular intervals to the measurement devices and the relationship between these known mole fractions and the measured signals is described by the calibration coefficients $a$ and $b$. This is done at regular intervals, because the relationship between known mole fractions and measured signals can change with time. Finally, this relationship is then carried over and applied to temporally proximal measured signals of ambient air.

$$c_{\text{cal}} = a + b \times s_{\text{meas}}.$$  

(2.4.1)

Measurements are affected by different sources of uncertainty. Uncertainty analysis needs to assess both random and systematic components. According to Andrews et al. [2014], three types of trace gas measurement
### Table 2.3: Parts of Längern-Hochwacht measurement system which was mostly replicated at Früebüel. The legend indicates unapparent parts in Figure 2.1. The lower half contains specific Swagelok® parts.

<table>
<thead>
<tr>
<th>Leg.</th>
<th>Name</th>
<th>No.</th>
<th>Description</th>
<th>Part Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>V1-6</td>
<td>PICARRO G2401 4-channel spectrometer</td>
<td>1</td>
<td>4-channel spectrometer</td>
<td></td>
</tr>
<tr>
<td></td>
<td>GEMS sensors 3-way solenoid valves</td>
<td>6</td>
<td>#10 - 32 UNF connections</td>
<td>GH3315-12VDC</td>
</tr>
<tr>
<td></td>
<td>Synflex 1300 100 m tubing</td>
<td>1</td>
<td>OD: 12mm ID: 8.2 mm</td>
<td>440.1012.210</td>
</tr>
<tr>
<td>FM1-2</td>
<td>Fisher Scientific Flowmeter</td>
<td>2</td>
<td>2-25 l/min 2 - 1/8&quot; NPT(F) connections</td>
<td>EW-32460-48</td>
</tr>
<tr>
<td></td>
<td>Scott-Marrin 30 l Aluminum cylinders</td>
<td>5</td>
<td>CGA590, Size 150</td>
<td>03S-150A-590B</td>
</tr>
<tr>
<td></td>
<td>Scott-Marrin Brass 2-Stage press.</td>
<td>5</td>
<td>0-75 PSI, 1/8&quot; outlet,</td>
<td>05-2SB30-590-D2T</td>
</tr>
<tr>
<td></td>
<td>reg.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P2</td>
<td>KNF Gas pump</td>
<td>1</td>
<td>&gt; 21 l/min, oil-free, w/ potentiometer</td>
<td>Type N 920</td>
</tr>
<tr>
<td>P1</td>
<td>Thomas pump</td>
<td>1</td>
<td>26 l/min</td>
<td>52061704</td>
</tr>
<tr>
<td>MFC</td>
<td>Voegtlin Mass flow controller</td>
<td>1</td>
<td>20-1000 1/min, G1/4&quot; inner thread</td>
<td>GSC-B4SA-BB23</td>
</tr>
<tr>
<td></td>
<td>Solberg MFG Inlet housing + 2 filters</td>
<td>2</td>
<td>2 1/2&quot; H x 6&quot; OD</td>
<td>F-15-050</td>
</tr>
<tr>
<td></td>
<td>APC Uninterruptible Power Supply</td>
<td>1</td>
<td>Back-UPS Pro 1200</td>
<td>BR1200GI</td>
</tr>
<tr>
<td></td>
<td>Hitachi 500GB harddisk</td>
<td>1</td>
<td></td>
<td>7K1000.D</td>
</tr>
<tr>
<td></td>
<td>Teflon tubing 2 m</td>
<td>1</td>
<td>lightning protection</td>
<td>FT-01 5096 5500</td>
</tr>
<tr>
<td></td>
<td>1m 1/8&quot; tubing</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>10m 1/16&quot; tubing</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>f</td>
<td>Dust filter</td>
<td>1</td>
<td>7 micron filter</td>
<td>SS-4FW-7</td>
</tr>
<tr>
<td>a</td>
<td>Tee</td>
<td>3</td>
<td>1/4&quot; all</td>
<td>SS-400-3</td>
</tr>
<tr>
<td>j</td>
<td>Tee</td>
<td>1</td>
<td>1/8&quot; all</td>
<td>SS-200-3</td>
</tr>
<tr>
<td>b</td>
<td>1/4&quot; Male Fitting NPT</td>
<td>4</td>
<td>1/4&quot; OD to 1/8&quot; NPT</td>
<td>B-400-1-2</td>
</tr>
<tr>
<td>h</td>
<td>1/8&quot; Male Fitting UNF 10-32</td>
<td>14</td>
<td>10-32 to 1/8&quot;</td>
<td>SS-200-1-0157</td>
</tr>
<tr>
<td>m</td>
<td>Reducer</td>
<td>8</td>
<td>1/8&quot; to 1/16&quot;</td>
<td>SS-100-R-2</td>
</tr>
<tr>
<td>e</td>
<td>1/4&quot; Male Fitting UNF 10-32</td>
<td>6</td>
<td>10-32 UNF to 1/4&quot;</td>
<td>SS-400-1-0256</td>
</tr>
<tr>
<td>g</td>
<td>Bulkhead Union - 1/4&quot;</td>
<td>2</td>
<td>1/4&quot; to 1/4&quot;</td>
<td>SS-400-61</td>
</tr>
<tr>
<td>c</td>
<td>Bulkhead Union - 1/4&quot; to 1/2&quot;</td>
<td>2</td>
<td>1/4&quot; to 1/2&quot;</td>
<td>SS-810-61-4</td>
</tr>
<tr>
<td>d</td>
<td>Reducer Union</td>
<td>2</td>
<td>12mm to 1/2&quot;</td>
<td>SS-12M0-6-8</td>
</tr>
<tr>
<td>i</td>
<td>Male Connector - MFC in/out</td>
<td>2</td>
<td>1/8&quot; Tube OD x 1/4&quot; Male ISO Par. Thread</td>
<td>SS-200-1-4RS</td>
</tr>
<tr>
<td>l</td>
<td>Carbon Steel Gasket</td>
<td>2</td>
<td>1/4&quot; ISO Parallel Thread (RS)</td>
<td>S-4-RS-2V</td>
</tr>
<tr>
<td>o</td>
<td>Inserts for synflex tubing</td>
<td>10</td>
<td>12mm OD and 8mm ID</td>
<td>SS-12M5-8M</td>
</tr>
<tr>
<td>p</td>
<td>Inserts for synflex tubing</td>
<td>50</td>
<td>1/4&quot; OD and 0.17mm ID</td>
<td>SS-405-170</td>
</tr>
<tr>
<td>k</td>
<td>Male NPT-Fitting</td>
<td>1</td>
<td>1/4&quot; NPT Connection with Pump</td>
<td>B-400-1-4</td>
</tr>
<tr>
<td>r</td>
<td>Female NPT-Bulkhead Union</td>
<td>2</td>
<td>Mount for inlets and reducer to 12mm</td>
<td>SS-12M0-71-8</td>
</tr>
<tr>
<td>q</td>
<td>Plug</td>
<td>1</td>
<td>1/8&quot; Plug (removed for 4th bottle)</td>
<td>SS-200-P</td>
</tr>
<tr>
<td>n</td>
<td>Cap</td>
<td>1</td>
<td>1/16&quot; cap for valve V6</td>
<td>SS-100-C</td>
</tr>
</tbody>
</table>

Uncertainty can be separately reported:
1. uncertainty related to the calibration scale $\sigma_{sc}$,

2. analytical uncertainty $\sigma_a$ consisting of non-random and random uncertainty,

3. standard error of the reported one-minute mean values composed of both instrument noise and atmospheric variability $\sigma_v$.

These uncertainties are used to specify the relative weight of each standard gas measurement, when calculating the calibration coefficients $a$ and $b$. The uncertainty of the calibration scale is constant in time and can be given separately, whereas the two other uncertainties vary with time and can be reported individually for every one-minute average. Random uncertainties can be reduced by temporal averaging, but systematic uncertainties can not be reduced in this way. The final, combined analytical uncertainty calculation considers both random uncertainties due to instrument noise and systematic uncertainties due to the uncertainty of the calibration, and other potential systematic uncertainties.

The uncertainty of the reference gas value determined in the laboratory $\sigma_{st}$ is a constant value, which includes the uncertainty of the mother standards used to transfer the scale, but may also contain the uncertainty of the scale ($\sigma_{sc}$). Here, however, these uncertainties of the parent standards were not included in the uncertainty treatment of the child standards (Table 2.2). That is, it is assumed that the mole fractions of the parent standards are known exactly. Uncertainties in the mother standards could easily be added at the end, if needed, as they apply to all observations in the same way. Uncertainties of the mole fractions of children standard gases are taken from the regression analysis performed to calibrate the employed measurement device.

We consider the contribution to the random part of the analytical uncertainty to come from the instrument’s precision or noise, defined here as the standard error of the one-minute mean of a reference gas measurement. Here, the precision $\sigma_p$ of a one-minute value is reported from a target gas measurement, which lasted $m$ minutes and contained $n$ different data points with the standard deviation $\sigma$. It is computed as:

$$\sigma_p = b \frac{\sigma}{\sqrt{n/m}},$$

(2.4.2)

where $b$ is the time-interpolated slope of the calibration curve.

Systematic uncertainty in the calibration coefficients comes from uncertainties in the reference gas measurements which are composed of the uncertainties $\sigma_{st}$ of the known reference gas and the uncertainty of the mean $\sigma_{s,meas}$ of the measured reference gas measurements. The uncertainty of the mean is calculated from the standard deviation $\sigma$ and number of measurements $N$ during the calibration as:

$$\sigma_{s,meas} = \frac{\sigma}{\sqrt{N}}.$$  

(2.4.3)

The systematic uncertainty here is introduced by the calculation of calibration coefficients also known as the calibration curve fitting uncertainty $\sigma_f$. It is computed as:

$$\sigma_f = \sqrt{\sigma_a^2 + s_{meas}^2 \sigma_b^2 + 2s_{meas} \sigma_{ab}},$$

(2.4.4)

where uncertainties of slope $\sigma_b$ and intercept $\sigma_a$, the measured signal $s_{meas}$, as well as their covariance $\sigma_{ab}$ are considered. This formulation computes the 67% confidence interval of the calibration curve (Figure 2.2).

The instrument’s precision and the uncertainty of the calibration curve’s fit are assumed to be independent. The total analytical uncertainty is the combination of the uncertainty due to instrument noise and the uncertainty of the fit and is computed as:
2.4. Measurement calibration and uncertainty

\[ \sigma_t = \sqrt{\sigma_p^2 + \sigma_f^2}. \]  \hspace{1cm} (2.4.5)

Other sources of uncertainty can be considered, such as water dilution, sampling biases, among others. We address these in Section 2.4.2. Finally, for ambient measurements in between two calibrations, the calibration coefficients of \( a \) and \( b \) are linearly interpolated to the given time, and the calibration curve fitting uncertainty \( \sigma_f \) is temporally propagated.

2.4.1 Calibration coefficients and uncertainty

Depending on the measurement device’s stability, different types of calibration can be considered:

1. “span”: to determine instrument response function (Figure 2.2),
2. “offset”: to account for short-term instrument baseline drifts in between span calibrations,
3. zero level: when baseline drift is problematic near zero.

What is referred to as a “span calibration”, hereafter, is the sequential measurement of at least two reference gases with low and high trace gas mole fractions which cover the range of ambient observed mole fractions. The goal here is to derive the measurement instrument’s response function in the range of observed variation. Ambient measurements outside the mole fraction range of the reference gases are flagged (see Section 2.4.6). As mentioned, we assume a fully linear instrument response and thus describe a span calibration as a line which may or may not be forced through zero as illustrated in Figure 2.2. Uncertainties of the measured signals (Figure 2.2, horizontal arrows) and the reference gas mole fractions (Figure 2.2, vertical arrows) need to be accounted for as they determine both the slope of the line and the confidence interval. The red lines in Figure 2.2 represent the 67% confidence range of the linear regression. This case of a non-zero offset depicts that the uncertainty of the calibration is smallest for mole fractions in between the low and high references and grows rapidly outside this range. This uncertainty of the calibration curve is computed for each measurement as an important element of the overall measurement uncertainty.

Given reference gas measurements of high and low reference gases, a two-point calibration with a free intercept can be performed. Here, the slope and intercept and their uncertainties and their covariance can be derived analytically and computed as:

\[ b = \frac{c_{st,2} - c_{st,1}}{s_{meas,2} - s_{meas,1}} \]  \hspace{1cm} (2.4.6)
\[ a = \frac{c_{st,1}s_{meas,1} - c_{st,2}s_{meas,2}}{s_{meas,2} - s_{meas,1}} \]  \hspace{1cm} (2.4.7)
\[ \sigma_b = b\sqrt{\frac{\sigma_{c,1}^2 + \sigma_{c,2}^2}{(c_{st,2} - c_{st,1})^2} + \frac{\sigma_{s,meas,1}^2 + \sigma_{s,meas,2}^2}{(s_{meas,2} - s_{meas,1})^2}} \]  \hspace{1cm} (2.4.8)
\[ \sigma_a = \sqrt{\frac{(c_{st,2} - c_{st,1})^2(s_{meas,2}^2\sigma_{s,meas,1}^2 + s_{meas,1}^2\sigma_{s,meas,2}^2)}{(s_{meas,2} - s_{meas,1})^4} + \frac{s_{meas,2}^2\sigma_{c,1}^2 + s_{meas,1}^2\sigma_{c,2}^2}{(s_{meas,2} - s_{meas,1})^2}}} \]  \hspace{1cm} (2.4.9)
\[ \sigma_{ab} = -\frac{(c_{st,2} - c_{st,1})^2(s_{meas,2}^2\sigma_{s,meas,1}^2 + s_{meas,1}^2\sigma_{s,meas,2}^2)}{(s_{meas,2} - s_{meas,1})^4} - \frac{s_{meas,2}^2\sigma_{c,1}^2 + s_{meas,1}^2\sigma_{c,2}^2}{(s_{meas,2} - s_{meas,1})^2}}, \]  \hspace{1cm} (2.4.10)

where \( i \) is the index of the reference gas, \( c_{st,i} \) is the known reference mole fraction, and \( s_{meas,2} \) is the measured signal.
Figure 2.2: Left: Calibration with offset $a$ and slope $b$. Standard errors of the calibration measurements are indicated by the horizontal arrows. Right: Similar to the left panel but the regression is forced through zero. Additional reference gas measurements may be included in both cases.

In a multiple-point calibration with free intercept or forced through origin, the values of $s_{\text{meas},i}$, $c_{\text{st},i}$, $\sigma_{s,\text{meas},i}$, and $\sigma_{c,\text{st},i}$ are used in weighted total least squares (WTLS) regression [Krystek and Anton, 2008], which takes into account the uncertainties of individual points in both coordinate directions. The WTLS algorithm directly yields $\sigma_a$, $\sigma_b$, and $\sigma_{ab}$.

In the case of a single point calibration forced through origin, the slope $b$ can be calculated from the ratio of $c_{\text{st}}$ to $s_{\text{meas}}$. The offset and its uncertainty are assumed to be zero, while the uncertainty of the slope is derived as:

$$\sigma_b = b \sqrt{\left(\frac{\sigma_{c,\text{st}}}{c_{\text{st}}}\right)^2 + \left(\frac{\sigma_{s,\text{meas}}}{s_{\text{meas}}}\right)^2}.$$  

(2.4.11)

In case of significant instrument drifts, it makes sense to perform additional, frequent ”offset calibrations” in between span calibrations. For this, a “working” gas is sampled immediately before or after span calibrations and in regular intervals in between two span calibrations. The mole fractions of this working gas do not need to be known accurately and can be done with gases housed in less expensive, high-volume cylinders. Specifically, this temporal adjustment to the set of span calibration coefficients is calculated as:

$$a_{\text{adj}}(t) = a(t) + c_{\text{cal, w, mid}}(t) - c_{\text{cal, int, w}}(t),$$  

(2.4.12)

where for a reference gas measurement at time $t$ in between two span calibrations at times $t_1$ and $t_2$, the slopes $b(t_1)$ and $b(t_2)$ are linearly interpolated to time $t$. At the time of a working gas measurement, the temporally interpolated, intermediate span offset $a_t$ is adjusted according to the difference between the interpolated, calibrated working gas mole fraction $c_{\text{cal, int, w}}(t)$ and the observed $c_{\text{cal, w, mid}}(t)$. These are also interpolated from times $t_1$ and $t_2$ to time $t$ (Figure 2.4).

### 2.4.2 Further uncertainty considerations

Other sources of uncertainty, identified and unidentified, can contribute to measurement uncertainty. Andrews et al. [2014] investigated analyzer baseline drift of PICARRO devices and found it to be small, and we therefore neglect this possible source of uncertainty.
Water vapor effects are a potential source of uncertainty in CRDS measurements. However, Rella et al. [2013] have shown that sufficient accuracy is maintained when measuring dry air CH\textsubscript{4} and CO\textsubscript{2} mole fractions in humid air. That is, the water correction performed by the PICARRO software works well. However, CO is only partially water corrected, but the algorithm for that is unknown. Chen et al. [2013] provide a solution to correct PICARRO CO measurements for water dilution and pressure broadening effects. In the CarboCount CH network, this uncertainty has been ignored.

Figure 2.3: Example sequence with one LOW and HIGH reference gas measurements between ambient measurements MEAS.

For a certain and variable amount of time after a valve switch, the air flowing to the measurement device is a mixture of previously and currently sampled gases (Figure 2.3). In the measurement system at Lägern-Hochwacht, the length of this equilibration time varies with the amount of residual water in the sampling line between the second valve (V2) and the measurement device, which varies with the difference between the ambient and measurement room’s temperature. At both Früebüiel and Lägern-Hochwacht, the amount of time necessary for equilibration was found to be 9 minutes, as determined visually by switching from ambient measurements to reference gas sampling. Therefore, all measurement data less than 9 minutes after valve transition are discarded. This time of the equilibration is transferred to ambient air measurements i.e. when switching from standard gas to ambient measurements or when switching sampling heights. Therefore, the uncertainty of equilibration due to proximity to a preceding valve transition is assumed to be zero. Due to a different setup at Beromünster, the equilibration time is much shorter with ∼2 minutes sufficing to flush the tubing [Berhanu et al., 2016].

Sampling bias describes the uncertainty introduced by the measurement system. For example, a leak in the tubing between the inlet and the measurement device would greatly affect gas samples. Initial and recurring, periodical leak tests during ambient measurements were carried out i.e. when the pressure inside the measurement system was less than ambient pressure. Directly after installation, highly concentrated CO (450 ppm) was applied to the outside of all fittings, while mole fractions were monitored. Later in the campaign, breathing onto the fittings was also unable to uncover any leaks. As a simple test later on in the campaign, the measurement inlet was plugged and a vacuum was successfully created between the inlet and measurement device. After these initial and recurring tests, it can be said that a significant sampling bias is likely absent.

2.4.3 Target gas measurements

"Target" reference gas measurements are not used for determining calibration coefficients and serve as an independent evaluation of the validity of the calibration procedure and of the representativeness of the estimated analytical uncertainty. The mole fractions of target gas references have to be stable over time. Target calibrations are treated in the same way as ambient measurements with regard to calibration. The difference between the known mole fraction and calibrated measured signals of the target gas provides a direct measure of the overall accuracy and overall validity of the calibration procedure.
In our case, target calibrations are additionally used to determine instrument precision or random analytical uncertainty of ambient air measurements. Furthermore, we report an independent measure of uncertainty based on target gas measurements. The difference between calibrated target gas measurements and known reference gas mole fractions is computed. These differences are reported directly as well as a temporally smoothed root mean squared error.

2.4.4 Calibration of ambient measurements

Ambient air samples are ideally collected in between two reference gas measurement cycles. Here, the calibration curve may have changed. It is assumed that such changes occur slowly with time. Therefore, temporally binning calibration curve coefficients are interpolated to the time of the measurements. Depending on the quality of the calibrations, it may be necessary to average coefficients from multiple calibrations.

![Figure 2.4: Schematic of temporal interpolation (top) or temporal averaging (bottom) of calibration coefficients from “span” calibrations binning the targeted processing time $t_{int}$.](image)

The two options are illustrated in Figure 2.4 for the span coefficient $b$. The upper panel of Figure 2.4 describes a simple linear interpolation of the slope $b$ between calibrations before and after the current time $t_{int}$. The lower panel describes the situation where a mean coefficient is computed from all calibrations within a given time range (e.g. ±3 days) of $t_{int}$. In the first case, calibration coefficients change continuously with time. In the second case, calibration coefficients are constant for a certain period but change stepwise whenever a new calibration appears in the moving time-window. Due to the high quality and the temporal stability of the measurement systems in CarboCount CH, the first approach has been implemented. If this approach appears to be suboptimal, a further option using local regression instead of a moving mean would possibly be better suited.

As in Equation (2.4.1), a measured signal $s_{meas,int}$ at time $t_{int}$ is calibrated as

$$c_{cal,t_{int}} = a_{t_{int}} + b_{t_{int}} s_{meas,t_{int}}.$$  \hspace{1cm} (2.4.13)
The linear interpolation of calibration coefficients to the time $t_{\text{int}}$ of a certain measurement is

$$w_2 = \frac{t_{\text{int}} - t_1}{t_2 - t_1}$$  \hspace{1cm} (2.4.14)$$
$$w_1 = 1 - w_2$$  \hspace{1cm} (2.4.15)$$
$$b_{t_{\text{int}}} = w_1 b_1 + w_2 b_2$$  \hspace{1cm} (2.4.16)$$
$$a_{t_{\text{int}}} = w_1 a_1 + w_2 a_2.$$  \hspace{1cm} (2.4.17)

where $t_{\text{int}}$ is in between times $t_1$ and $t_2$, and the weights $w$ depend on the temporal distance from times $t_1$ and $t_2$. The interpolation of the related uncertainties is computed as:

$$\sigma_{a,t_{\text{int}}} = \sqrt{w_1^2 \sigma_{a,1}^2 + w_2^2 \sigma_{a,2}^2}$$  \hspace{1cm} (2.4.18)$$
$$\sigma_{b,t_{\text{int}}} = \sqrt{w_1^2 \sigma_{b,1}^2 + w_2^2 \sigma_{b,2}^2}$$  \hspace{1cm} (2.4.19)$$
$$\sigma_{ab,t_{\text{int}}} = w_1^2 \sigma_{ab,1} + w_2^2 \sigma_{ab,2}.$$  \hspace{1cm} (2.4.20)

### 2.4.4.1 Observed variability

Observed mole fractions can vary much during one-minute intervals. This variability is the combination of uncertainty introduced by the measurement system and true atmospheric variability during the one-minute averaging period. The standard error of a one-minute mean value $\sigma_{s,v}$ is the standard deviation $\sigma_v$ divided by the square root of the number $N$ of all samples during a one-minute interval:

$$\sigma_{s,v} = \frac{\sigma_v}{\sqrt{N}}.$$  \hspace{1cm} (2.4.21)

This uncertainty is typically larger than the precision $\sigma_p$. Because the random analytical uncertainty has been estimated for one-minute averages, true atmospheric variability can then be estimated. Therefore, as mentioned, target gas measurements are used to determine the random analytical uncertainty of ambient air measurements.

### 2.4.5 Higher time aggregates

Short-term temporal variability is of random nature and therefore not interesting in the context of regional-scale modeling. The variation due to random atmospheric variability can also be reduced with temporal averaging. For efficiency, higher time aggregates are computed from the averaged, calibrated one-minute data. The combined uncertainty of these time aggregates needs to consider random and non-random components of the one-minute values and the uncertainty due to incomplete temporal coverage. The temporal average is given by:

$$\bar{c} = \frac{1}{N} \sum_{i} c_{\text{cal},i},$$  \hspace{1cm} (2.4.22)$$

and its uncertainty is composed of the analytical uncertainty $\sigma_{c,a}$ and, eventually, the uncertainty due to missing values $\sigma_u$ (under-sampling):
The analytical uncertainty of the mean can be calculated from the random $\sigma_p$ and the non-random $\sigma_f$ contributions of the analytical uncertainty of the individual one-minute measurements. When non-random uncertainty is not constant over time, the total analytical uncertainty of the mean is:

$$\sigma_{c,a}^2 = \frac{1}{N^2} \sum_i \sigma_{a,p,i}^2 + \frac{1}{N} \sum_i \sigma_{a,f,i}^2.$$  

(2.4.24)

The uncertainty due to missing values $\sigma_u$ is calculated as:

$$\sigma_u^2 = \left(1 - \frac{N}{N_{\text{max}}}\right) \frac{1}{N} S^2$$  

(2.4.25)

$$S^2 = \frac{1}{N-1} \sum_i \left(c_{\text{cal},i} - \bar{c}\right)^2,$$  

(2.4.26)

where $N_{\text{max}}$ is the number of samples that could have been taken by continuous, uninterrupted sampling, $N$ is the number of measurements made, and $S$ is the variance observed during the aggregation interval. To precisely specify the observed variability for higher time aggregates (ten-minute, hourly, and three-hourly) of period $K$, the period’s standard error of the mean $\sigma_{s,K}$ should also be calculated from the raw sampling data, in the same manner as for the one-minute aggregates.

Ideally, the observed variability of higher time aggregates should be calculated from the high-frequency measured signals. For efficiency, this can also be approximated from the one-minute aggregates. This requires that the observed variability in each one-minute interval $\sigma_{s,1,i}$, the standard deviation of the one-minute averages, the number of measured signals for each one-minute interval $n_{1,i}$, and the one-minute mean values $c_{1,i}$ are available. Then $\sigma_{s,K}$ can be calculated as:

$$\sigma_{s,K} = \sqrt{\sigma_{s,v}^2 + \sigma_{s,p}^2}$$  

(2.4.27)

$$\sigma_{s,v} = \frac{\sum_i (c_{\text{cal},i} - \bar{c})^2}{N - 1}$$  

(2.4.28)

$$\sigma_{s,p} = \frac{\sum_i \sigma_{s,1,i}^2}{m},$$  

(2.4.29)

where $m$ is the number of one-minute averages included in the higher time aggregate, $\sigma_{s,v}$ is the uncertainty of the one-minute averages, and $\sigma_{s,p}$ is the standard error of the one-minute averages. In a situation with a constant mean (little variability on time scales beyond one-minute) this approximation appears to overestimate the directly observed variability. When there is high variability, this formulation is a good approximation. The observed variability of higher time aggregates is expected to be larger than the analytical uncertainty of higher time aggregates.

### 2.4.6 Quality control

Even with a well-functioning measurement device, erroneous values still arise for reasons listed in Table 2.4. Automatic exclusion of erroneous values is partially applicable, but the need for manual inspection still exists. This requires careful consideration and justification to exclude anomalous but otherwise undisturbed
### Table 2.4: Flag table for CarboCount CH measurement data.

<table>
<thead>
<tr>
<th>Code</th>
<th>Description</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>No event compromising data quality or precision</td>
<td>Highest data quality such that a calibration is near, the precision is high, the measured mole fraction lies within the range of reference gas mole fractions.</td>
</tr>
<tr>
<td>1</td>
<td>Uncertainty of a value is greater than 1 per mil</td>
<td>The calculated uncertainty does not meet quality requirements.</td>
</tr>
<tr>
<td>2</td>
<td>Measured mole fraction is outside of the calibration mole fraction range</td>
<td>Measured mole fractions outside the range spanned by the low and high reference gas calibration mole fractions, or one-point calibration.</td>
</tr>
<tr>
<td>4</td>
<td>Reference gas measurements are far removed in time</td>
<td>The nearest calibration coefficients are temporally interpolated.</td>
</tr>
<tr>
<td>8</td>
<td>Critically low average number of measurements</td>
<td>Poor quality data, the device may measure more that one gas and may not measure each gas regularly.</td>
</tr>
<tr>
<td>16</td>
<td>Unassigned</td>
<td></td>
</tr>
<tr>
<td>32</td>
<td>Unassigned</td>
<td></td>
</tr>
<tr>
<td>64</td>
<td>Unassigned</td>
<td></td>
</tr>
<tr>
<td>128</td>
<td>Data are not usable</td>
<td>Due to work done on the device, tower or other activities that may contaminate samples.</td>
</tr>
<tr>
<td>NaN</td>
<td>Device did not measure or data occurred in a valve transition</td>
<td>Due to power loss, valve change etc., the data are not present.</td>
</tr>
</tbody>
</table>

measures. The flagging system described in Table 2.4 is a result of the uncertainties considered and encountered during the CarboCount site operations. It is based on a binary system which allows combining different flags from co-occurring events into a single number. This flagging system is applied to each measured gas separately. It is somewhat automated, but manual application of flagging system to ambient and calibration measurements is nonetheless necessary to assure good data quality.

### 2.5 Ambient and reference gas measurements

#### 2.5.1 Uncertainty estimates

The ability to accurately estimate the known mole fraction of the target reference gas throughout the measurement campaign with the calibration routines lends credibility to its effectiveness. The target uncertainties as reported here demonstrate the validity of our calibration routine (Figure 2.5, summaries in Table 2.5). Calibrated target gas measurements of CO$_2$ and CH$_4$ typically deviate $\sim 0.07$ and $\sim 0.0005$ ppm from known target reference gas mole fractions, which implies compatibility with WMO guidelines of $\pm 0.1$ ppm and $\pm 0.002$ ppm, respectively. Richardson et al. [2012] attained similar results during the Mid-Continental Intensive measurement campaign with PICARRO analyzers.

Table 2.5: Root mean square error (in ppm) between known and calibrated target reference gas mole fractions during their period of measurement (see Figure 2.5).

<table>
<thead>
<tr>
<th>Site</th>
<th>CO$_2$</th>
<th>CH$_4$</th>
<th>CO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beromünster</td>
<td>0.061</td>
<td>0.0018</td>
<td>0.0037</td>
</tr>
<tr>
<td>Früebüel</td>
<td>0.079</td>
<td>0.0004</td>
<td></td>
</tr>
<tr>
<td>Gimmiz</td>
<td>0.077</td>
<td>0.00029</td>
<td></td>
</tr>
<tr>
<td>Lägern-Hochwacht</td>
<td>0.049</td>
<td>0.00027</td>
<td>0.0025</td>
</tr>
</tbody>
</table>

Differences between sites are due mainly to differences in reference gas sampling routines. At Beromünster,
Figure 2.5: Target gas calibration results at the CarboCount CH sites. Individual differences between known and calibrated target gas molar ratios are plotted, with independent analytical and target uncertainty bands (±).

shorter sampling times of 6 minutes (4 minutes after valve change) likely result in more variable target gas measurements, which contrasts with that at Früebüel or Lägern-Hochwacht of 15 minutes (6 minutes after valve change). Furthermore, it appears that some target gas mole fractions could be known better, such as the CO\textsubscript{2} mole fraction at Gimmiz. Similarly, a target gas bottle change at Früebüel during the summer of 2014 also influenced the CH\textsubscript{4} target uncertainty, leading to a small bias between known and calibrated mole fractions. Here, it may be that the determination of the child cylinder is not as certain as thought. These small deviations are still well within WMO quality requirements, but illuminate the possible problems with relying on target gas measurements for uncertainty estimation.

CO measurements at Beromünster and Lägern-Hochwacht, on the other hand, include significant random systematic uncertainty due to the measurement device. Nonetheless, calibrated target measurements typically
deviate $\sim 0.003$ ppm from known target gas mole fractions. Here, the quality of these measurements fulfill WMO guidelines extended compatibility goals of $\pm 0.005$ ppm, but fail to meet the stricter compatibility goals of $\pm 0.002$ ppm.

Directly estimating the analytical uncertainty grossly underestimates the apparent uncertainty of all gases, suggesting an additional unconsidered source of uncertainty. The ignorance of the uncertainties of scale and of the determined mole fractions of the parent standards may contribute the necessary constant uncertainties necessary to remove a possible low bias of the estimated uncertainties. Also likely would be contributions of baseline drift and water correction uncertainties inherent to the PICARRO devices. Together, these uncertainty contributions would inflate the estimated uncertainties. Furthermore, we likely do not have realistic estimates for the CO measurements at Gimmiz, because the analytical uncertainties are not representative. Investigation is necessary to improve calibration and uncertainty estimation in general and especially the uncertainty of the CO measurements at Gimmiz, where target gas measurements were not carried out for CO.

Altogether, these observed time series are of good quality (Table 2.5), especially with regard to observed regional signal variability (please compare Figure 2.6 to the MLO time-series in Figure 1.4). As emphasized by Tans and Zellweger [2014], regional scale modeling studies need to maintain consistency of reference scales within the measurement network.

### 2.5.2 Measurement time series

The network’s atmospheric carbon measurements exhibit large seasonal and daily variability. The seasonal CO$_2$ cycle is most pronounced, but is also considerable in both CO and CH$_4$. For example, the trend of increasing CO$_2$ mole fractions is visible from the lowest mole fractions (Figure 2.6), but is small relative to the annual range of observed mole fractions.

The diurnal variability is also very large, and is greatest in summer at Gimmiz (Figure 2.7). Here, the diurnal variability is present also during winter, and is therefore most likely due to ABL dynamics, as will be discussed in more detail in the following Chapter.

### 2.6 Practical monitoring considerations

With the goal of meeting the WMO’s greenhouse gas measurement guidelines [Tans and Zellweger, 2014], while keeping maintenance costs minimal, measurement system failures need to be avoided and repetitive tasks need to be automated. To meet these goals within the CarboCount project, a considerable initial investment was required. This has been successful in keeping further costs low. The following contains what was learned from the measurements made at Lägern-Hochwacht, and to a large degree also at Friebibel.

Filling and determination of reference gas bottles can be a cumbersome and costly task, especially if reference gases need to be calibrated by an external laboratory. Measurement of reference gases for span calibration was initially frequent at the CarboCount sites: every 20 hours a target gas measurement and every 40 hours a measurement of high and low mole fraction reference gases were sampled for 15 minutes each. On February 6, 2014, a less frequent reference gas measurement routine was implemented, measuring target, low, and high reference gases every 100 hours. Here, the target reference gas was sequentially sampled 5 hours later in the sampling cycle i.e. directly after the span reference measurement, then 5 hours afterwards, then 10 hours afterwards, and so on. The target gas reference measurement steps through the calibration cycle and time of day to possibly uncover the effect of changing room temperature. As can be seen in Figure 2.5, the larger temporal distance from span reference measurements and seasonally varying room temperature effects likely
Figure 2.6: Atmospheric carbon measurements (CO$_2$, CH$_4$, & CO) during afternoon (1200-1500 UTC, 1300-1600 LT) at the CarboCount CH sites. The Beromünster data are from the highest sampling height (212 m).

did not affect target uncertainty. Therefore, the infrequent sampling and use of reference gas greatly reduces costs, but appeared to not have compromised data quality. Furthermore, Beromünster span calibration gas sampling is carried out weekly, which also does not seem to affect data quality. A longer calibration interval may be considered in the future, but would need testing, which could be performed with currently available standard gas measurements.

2.6.1 Equipment

Several problems of the measurement systems were avoided or solved after discovery, and current equipment recommendations are in Table 2.3. First and foremost, the quality of the standard PICARRO pumps was
### 2.6. Practical monitoring considerations

**Figure 2.7:** Seasonal average daily cycles of observed atmospheric carbon mole fractions from the CarboCount CH sites. Uncertainty bands correspond to ±1σ at the respective time of day. Time zone is UTC.

Not sufficient for sustained monitoring. Within four months of deployment, three of four pumps had failed. Most pumps were replaced with higher-quality, stronger pumps, which have operated reliably since.

After the initial pump failure at Lägern-Hochwacht, the measurement device began to measure some gases less frequently (1-2 min⁻¹ vs. 20-25 min⁻¹). In order to solve this problem, one of the laser’s voltage needed to be manually adjusted. Since then, this procedure was carried out three more times, but has not been necessary since April 2014. To uncover this problem, it is necessary to monitor the number of measurements being made or monitor the raw data file sizes. Both of these tests can only be done using the raw data files, and it is therefore not advisable to opt for the temporally averaged “DataLog_User_Sync” PICARRO data.

In order to avoid a potential failure of the computer’s hard disk as well as to ensure sufficient storage capacity, the stock hard disk was replaced with a higher capacity hard disk. Initially, the valve control board could
power only five of six valves, which also needed replacement.

The three-stage brass regulators repeatedly stopped allowing airflow. This was fixed by removing the bonnet nut on the back of the main regulator’s body and adjusting the underlying screw nut. Further measurement campaigns will likely not use these pressure regulators.

### 2.6.2 Operational data processing considerations

An automated data transfer and data control system was set up to retrieve measurements from the field-deployed instrument in near real-time. Data was sent hourly to an sFTP server via broadband Internet connection. A broadband USB Internet connection is regularly toggled on and off, in order to not overstrain the USB-broadband Internet stick. New data are sent with `rsync` (Cygwin). Data older than three months are moved to a non-standard file location, in order to reduce the computational strain of retrieving and comparing file attributes. Three-hourly automatic checks are carried out. First, notifications are sent if data has not been received in the last three hours. Second, file sizes are checked, for reasons previously discussed.

Upon initial aggregation to one-minute values, data after a valve change are discarded and remaining data are then split into ambient and reference gas measurements. For this, it was practical to define site- and time-dependent valve information, which specifies what is being sampled (valve configuration) and the time necessary for measured signals to equilibrate after valve change (Figure 2.3). This form of site- and time-dependent valve information greatly eases data processing when valve configuration changes take place, such as reference gas bottle changes. Finally, due to changes in the reference scale or drifts in reference gas mole fractions during the measurement campaign, this information greatly facilitates retroactive calibration.

Furthermore, time and site-dependent device information was defined, which specifies the serial number of the device, period of deployment, the measured gas species, and possible erroneous values. This also eases data processing, when the devices are replaced, or to account for certain anomalies in the data that are specific to a certain device and gas species. Most importantly, device changes indicate a change in the calibration coefficients, which implies no temporal interpolation of these temporally adjacent but different sets of calibration coefficients.

These forms of information organization constitute a minimum amount of measurement site documentation in order to make the processing calibration of CarboCount CH affordable and timely. Examples of this and an overview of the code to process the measurement data from the network can be found in Appendix A (specifically Tables A.1 & A.2).

### 2.7 Conclusions

Precise and accurate measurement of atmospheric carbon constitutes an important step toward understanding carbon fluxes between the atmosphere and Earth’s surface in a top-down modeling framework. Here, we described and discussed the measurement system of Lägern-Hochwacht, a CarboCount CH Swiss Siner gia Project measurement site. Then, we described and discussed the measurement uncertainty estimation CarboCount CH sites: Beromünster, Früebüel, Gimmiz, and Lägern-Hochwacht.

At Lägern-Hochwacht from 2012-08-23 to 2015-10-01, the measurement system operated 99 % of the time. The single major break in measurements was due to a pump failure. A similar measurement system at Früebüel also reported a good temporal coverage (96 % temporal coverage). The few measurement gaps at Früebüel were due to the failure of measurement device’s pump and power outages. The need for long equilibration times of 9 minutes after a valve switch to reference gas measurement are reconciled by the infrequent calibrations, as well as by the robustness and simplicity of the measurement system.
Across all sites, we report CO$_2$ and CH$_4$ measurements calibrated against the corresponding international reference scales. The calibration of independently measured target reference gases suggests an accuracy of the CO$_2$ and CH$_4$ measurements $\sim$0.07 ppm and $\sim$0.0004 ppm. Except for Früebüel, CO was also continuously measured, was similarly calibrated, and was determined to have a determined accuracy of $\sim$0.004 ppm at Beromünster and Lägern-Hochwacht. This is mostly due to the poor instrument precision. This can be lessened with temporal averaging. Further investigation is necessary of the calibration and uncertainty estimation of the CO measurements at Gimmiz, where target gas measurements were not carried out.
Chapter 3

The CarboCount CH sites:
characterization of a dense greenhouse
gas observation network

Published in Atmospheric Chemistry and Physics, 15, 11147–11164, 2015

Authors: Brian Oney\textsuperscript{1,2}, Stephan Henne\textsuperscript{1}, Nicolas Gruber\textsuperscript{2,3}, Markus Leuenberger\textsuperscript{4}, Ines Bamberger\textsuperscript{5,a}, Werner Eugster\textsuperscript{5}, Dominik Brunner\textsuperscript{1,2}

\textsuperscript{1} Lab. for Air Pollution/Environmental Technology, Dübendorf, Switzerland
\textsuperscript{2} ETH Zurich, Center for Climate Systems Modeling, Zurich, Switzerland
\textsuperscript{3} ETH Zurich, Inst. of Biogeochemistry and Pollutant Dynamics, Zurich, Switzerland
\textsuperscript{4} Univ. of Bern, Physics Inst., Climate and Environmental Division, and Oeschger Centre for Climate Change Research, Bern, Switzerland
\textsuperscript{5} ETH Zurich, Inst. of Agricultural Sciences, Zurich, Switzerland
\textsuperscript{a} now at: Karlsruhe Institute of Technology, Institute of Meteorology and Climate Research – Atmospheric Environmental Research, Garmisch-Partenkirchen, Germany
3.1 Abstract

We describe a new rural network of four densely placed (<100 km apart), continuous atmospheric carbon (CO$_2$, CH$_4$, and CO) measurement sites in north-central Switzerland and analyze its suitability for regional-scale (~100–500 km) carbon flux studies. We characterize each site for the period from March 2013 to February 2014 by analyzing surrounding land cover, observed local meteorology, and sensitivity to surface fluxes, as simulated with the Lagrangian particle dispersion model FLEXPART-COSMO (FLEXible PARTicle dispersion model-Consortium for Small-Scale Modeling).

The Beromünster measurements are made on a tall tower (212 m) located on a gentle hill. At Beromünster, regional CO$_2$ signals (measurement minus background) vary diurnally from $-4$ to $+4$ ppmv, on average, and are simulated to come from nearly the entire Swiss Plateau, where 50% of surface influence is simulated to be within 130–260 km distance. The Fruebuel site measurements are made 4 m above ground on the flank of a gently sloping mountain. Nearby (<50 km) pasture and forest fluxes exert the most simulated surface influence, except during convective summertime days when the site is mainly influenced by the eastern Swiss Plateau, which results in summertime regional CO$_2$ signals varying diurnally from $-5$ to $+12$ ppmv and elevated summer daytime CH$_4$ signals (+30 ppbv above other sites). The Gimmiz site measurements are made on a small tower (32 m) in flat terrain. Here, strong summertime regional signals ($-5$ to $+60$ ppmv CO$_2$) stem from large, nearby (<50 km) crop and anthropogenic fluxes of the Seeland region, except during warm or windy days when simulated surface influence is of regional scale (<250 km). The Lägern-Hochwacht measurements are made on a small tower (32 m) on top of the steep Lägern crest, where simulated surface influence is typically of regional scale (130–300 km) causing summertime regional signals to vary from $-5$ to $+8$ ppmv CO$_2$. Here, considerable anthropogenic influence from the nearby industrialized region near Zurich causes the average wintertime regional CO$_2$ signals to be 5 ppmv above the regional signals simultaneously measured at the Fruebuel site.

We find that the suitability of the data sets from our current observation network for regional carbon budgeting studies largely depends on the ability of the high-resolution (2 km) atmospheric transport model to correctly capture the temporal dynamics of the stratification of the lower atmosphere at the different sites. The current version of the atmospheric transport model captures these dynamics well, but it clearly reaches its limits at the sites in steep topography and at the sites that generally remain in the surface layer. Trace gas transport and inverse modeling studies will be necessary to determine the impact of these limitations on our ability to derive reliable regional-scale carbon flux estimates in the complex Swiss landscape.

3.2 Introduction

The exchange of carbon dioxide (CO$_2$) with the terrestrial biosphere dominates the observed year-to-year variability in the global carbon sinks [Battle et al., 2000; Sarmiento et al., 2010; Le Quéré et al., 2010] even though land surfaces cover only 30% of Earth’s surface area. Yet, our ability to quantify this variability in the net terrestrial carbon flux directly from observations has remained limited [Ciais et al., 2014]. As a result, in most attempts to determine the global carbon budget, the net terrestrial carbon flux is estimated as the difference between the observed atmospheric carbon growth rate, and the sum of oceanic and anthropogenic carbon fluxes [Sarmiento et al., 2010; Le Quéré et al., 2013]. Additionally, the lack of understanding of the feedbacks between climate change and the terrestrial biosphere translates into one of the greatest uncertainties of future climate change projections [Heimann and Reichstein, 2008]. An important step toward the reduction of this uncertainty is a better understanding of how the terrestrial biosphere responds to climatic fluctuations and trends. As the processes governing this response are inherently local to regional, this requires the determination of terrestrial carbon fluxes at high spatial resolution [Gerbig et al., 2009].
The currently employed methods to determine terrestrial carbon fluxes from observations include global networks of background CO\textsubscript{2} measurements [Tans et al., 1996] that permit the determination of fluxes at continental scales [Gerbig et al., 2003b] and eddy covariance-based surface flux measurements that have a small-scale (\sim 1 \text{ km}) footprint [Baldocchi et al., 2001]. This leaves an obvious gap at intermediate scales (10–10\,000 km), which clearly needs to be filled in order to reliably determine the terrestrial carbon budget [Ciais et al., 2014]. The establishment of the North American [Bakwin et al., 1998] and European [http://www.chiotto.org/; Vermeulen et al., 2004] tall tower networks represented a big step in this direction, but the high spatial heterogeneity of land cover and the correspondingly large variations in the CO\textsubscript{2} fluxes require even denser observation networks, especially in order to target regional-scale (< 1000 km) carbon fluxes [Dolman et al., 2009; Lawaux et al., 2012a]. The spatial density of a measurement network required to resolve the spatial distribution of carbon fluxes is dependent on the region of interest and the corresponding carbon flux signatures, and largely remains an open question [Groenendijk et al., 2011; Lawaux et al., 2012a].
campaign attempted to oversample the US upper midwest over a longer period of time [2007–2009; Miles et al., 2012], but even with an average distance of approximately 188 km between eight towers, Lauvaux et al. [2012a] found that the spatial density of the measurement network was insufficient to consistently retrieve the spatial distribution of carbon fluxes.

The CarboCount CH project (http://www.carbocount.ch) was designed to overcome some of these limitations. It intends to quantify terrestrial carbon fluxes at high temporal and spatial resolutions for multiple years through a combination of greenhouse gas concentration measurements and high-resolution atmospheric transport modeling. Four greenhouse gas measurement sites have been established in the Swiss Plateau (Fig. 3.1), which is a densely settled, partly flat and hilly region between the Alps and Jura mountains approximately 50 km by 200 km in size with an average altitude of ∼450 m a.s.l. (above sea level). The measurement sites are located in rural areas and the average distance between sites is 85 km. The main goal of the CarboCount CH project is to better understand surface fluxes of carbon, which for carbon dioxide (CO$_2$) mainly consist of anthropogenic emissions and biospheric activity, and for methane (CH$_4$) mainly (∼80%) of agricultural emissions [Hiller et al., 2014].

The CarboCount CH measurement network includes measurement sites in complex terrain, which warrants the use of high-resolution transport models [Pillai et al., 2011]. A measurement site’s local environment, especially the topography and land cover within a 3 km distance, exerts influence on the local meteorology and thereby largely determines the local surface influence on observed trace gas concentrations [Vesala et al., 2008]. Currently, most surface flux estimation studies use only afternoon measurements from sites in flat terrain when the ABL (atmospheric boundary layer) is thickest and well-mixed to reduce the sensitivity to errors in the representation of the ABL by the atmospheric transport models [Gerbig et al., 2009; Pillai et al., 2012; Kretschmer et al., 2014]. At mountain sites, conversely, nighttime or early morning measurements above the stable ABL are preferentially used due to the difficulties in correctly representing the daytime convective ABL above steep terrain. In inverse modeling studies using coarse resolution models, measurements from mountain sites are usually discarded all together.

The purpose of this study is to characterize the CarboCount CH observation network. We describe the local environment of each of the four measurement sites and investigate how much the local environment influences meteorology and greenhouse gas measurements. Furthermore, we assess the sensitivity of each measurement site to regional surface fluxes with the Lagrangian particle dispersion model FLEXPART-COSMO (FLEXible PARTICle dispersion model-Consortium for Small-Scale Modeling). Due to the dependence on the employed atmospheric transport model to represent local and regional surface influences, we evaluate simulated meteorology in order to uncover possible transport simulation problems. Thus, we assess the information content of each site’s measurements and establish potential guidelines for future transport and inverse modeling studies.

### 3.3 Data and methods

#### 3.3.1 Measurement data

The four measurement sites of the CarboCount CH network (Fig. 3.1, Table 3.1) were equipped with PICARRO (Santa Clara, California, USA) cavity ring-down spectrometers for greenhouse gases measurements [Crosson, 2008; Rella et al., 2013]. Additionally, meteorological variables including horizontal wind, humidity, dewpoint, and temperature were measured at all four sites. At Beromünster (BEO), air was sampled from five different heights (212, 132, 72, 45, and 12 m a.g.l. – above ground level), and carbon dioxide (CO$_2$), methane (CH$_4$), water (H$_2$O) and carbon monoxide (CO) were measured with a PICARRO G2401 analyzer. Meteorology was measured at all heights with Gill MetPak II remote weather stations (Gill Instruments Ltd., Hampshire, UK). Data used in this study were taken from the highest height. At Gimmiz (GIM), CO$_2$, CH$_4$, ...
3.3. Data and methods

Table 3.1: Details of the four measurement sites of the CarboCount CH network. From left to right: the site name, the site code, measurement commencement date, the measurement height(s), measured trace gases, the site’s altitude (m a.s.l.), and the geographic site locations.

<table>
<thead>
<tr>
<th>Site</th>
<th>Code</th>
<th>Date</th>
<th>Gases</th>
<th>Device</th>
<th>Height(s)</th>
<th>Alt.</th>
<th>Lat., Lon.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beromünster</td>
<td>BEO</td>
<td>3 Nov 2012</td>
<td>CO$_2$, CH$_4$</td>
<td>PICARRO G2401</td>
<td>212, 132,</td>
<td>797</td>
<td>47.1896, 8.1755</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CO, H$_2$O</td>
<td>G2311-f</td>
<td>45, 12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Früebüel</td>
<td>FRU</td>
<td>21 Nov 2012</td>
<td>CO$_2$, CH$_4$, H$_2$O</td>
<td>PICARRO G2301</td>
<td>4</td>
<td>982</td>
<td>47.1158, 8.5378</td>
</tr>
<tr>
<td>Gimmiz</td>
<td>GIM</td>
<td>22 Feb 2013</td>
<td>CO$_2$, CH$_4$, H$_2$O, CO</td>
<td>PICARRO G2301</td>
<td>32</td>
<td>443</td>
<td>47.0536, 7.2480</td>
</tr>
<tr>
<td>Lägern-Hochwacht</td>
<td>LAE</td>
<td>23 Aug 2012</td>
<td>CO$_2$, CH$_4$, CO, H$_2$O</td>
<td>PICARRO G2401</td>
<td>32</td>
<td>840</td>
<td>47.4822, 8.3973</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>APMA 360</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

and H$_2$O concentrations were measured with a PICARRO G2301 and CO with a Horiba APMA360, all of which were taken at 32 m a.g.l. The same meteorology instrumentation at Beromünster was employed here. At Früebüel (FRU), which is also a Swiss FluxNet site [Zeeman et al., 2010], CO$_2$, CH$_4$, and H$_2$O concentrations were measured with a PICARRO G2301 at 4 m a.g.l. and meteorology variables were measured at a height of 2 m a.g.l. [Bamberger et al., 2016]. On the 32 m tower at Lägern-Hochwacht (LAЕ), CO$_2$, CH$_4$, CO, and H$_2$O concentrations were measured with a PICARRO G2401. Here, MeteoSwiss measured the following meteorological variables: wind (Vaisala WA25 Wind Set, Vaisala Inc., Helsinki, Finland), temperature and humidity (Vaisala HMP155), and pressure (Vaisala PTB-220).

CO$_2$ and CH$_4$ measurements were calibrated against the corresponding international reference scales: WMO X2007 for CO$_2$ [Zhao and Tans, 2006] and WMO X2004 for CH$_4$ [Dlugokencky et al., 2005]. The calibration of target gas measurements – not used for the determination of calibration coefficients – suggests an accuracy of the CO$_2$ and CH$_4$ measurements of ~0.07 ppmv and ~0.5 ppbv, respectively, computed as the 10-day averaging window RMSE (root mean square error) of individual target measurements during the study period. Measurements were summarized to hourly averages for the 1-year period from 1 March 2013 to 28 February 2014 considered in this study.

In order to derive regional signals of the trace gas concentrations at each site, a background concentration was estimated and subtracted from the measurements. The background concentration was estimated using the “robust extraction of baseline signal” method [Ruckstuhl et al., 2012] from measurements at the high Alpine research station Jungfraujoch, which mainly samples free tropospheric air [Zellweger et al., 2003; Henne et al., 2010]. Measurements at Jungfraujoch were made with a PICARRO G2401 analyzer and referenced to the same calibration scales [Schibig et al., 2015]. We investigated the validity of the assumption that this background concentration estimate corresponds to background concentrations by comparing with NOAA’s Marine Boundary Layer reference (MBL$^1$) at the corresponding latitude. We found them to be very similar (not shown), but the annual peak-to-peak amplitude of the Jungfraujoch background concentration estimate (~8 ppmv) is less than that of the MBL estimate (~14 ppmv). However, the qualitative purpose of considering regional signals in this study remains unaffected by these differences.

For Switzerland, agricultural CH$_4$ emissions constitute more than 80% of the total emissions and show high spatial variation, but their temporal variations are small and predominantly seasonal [Hütt et al., 2014] due to seasonal relocation of cattle. Therefore, within a season, variations of methane concentrations serve as an atmospheric tracer and specifically as a proxy for the effect of the diurnally varying ABL.

$^1$http://www.esrl.noaa.gov/gmd/ccgg/mbl/mbl.html.
3.3.2 COSMO meteorology and FLEXPART-COSMO simulations

The sensitivity of the four measurement sites to upwind surface fluxes was assessed using a Lagrangian particle dispersion model (LPDM) driven by meteorological fields from a high-resolution numerical weather prediction (NWP) model. As input for the transport simulations we used hourly analysis fields from the operational weather forecast system of the Swiss national weather service, MeteoSwiss, which is based on the NWP model COSMO. COSMO is a state-of-the-art non-hydrostatic, limited-area NWP model [Baldauf et al., 2011] developed by the Consortium for Small-Scale Modeling under the guidance of the German weather service (DWD; Offenbach, Germany). It is the operational weather forecast model of the national weather services in Germany, Greece, Italy, Poland, Romania, and Russia. In the version COSMO-CLM (Climate Limited area Modeling), optimized for climate simulations, it is used by a wide community of regional climate modelers (http://www.clm-community.eu).

The operational setup for COSMO simulations of MeteoSwiss includes two nested domains. The outer domain covers large parts of Europe at about 7 km × 7 km resolution (COSMO-7). The inner domain covers the Alpine region including Switzerland, Austria and parts of Germany, France and Italy at about 2 km × 2 km resolution (COSMO-2). COSMO-7 is driven by European Centre for Medium Range Weather Forecast (ECMWF) analysis fields of ECMWF’s global IFS (Integrated Forecasting System) model and provides the boundary conditions for the COSMO-2 simulation. Hourly analysis fields are produced for both model domains applying the observational nudging technique [Schraff, 1997] to surface observations of pressure, relative humidity and wind. Similarly, measurements of the same variables plus ambient temperature as taken with sondes and profilers are also assimilated. In addition, a latent heat nudging scheme [Stephan et al., 2008] is used for the COSMO-2 domain to incorporate radar derived rain rates.

COSMO-2 provides the high resolution necessary to represent the complex topography in the Alpine area and the topography-induced mesoscale weather patterns. In order to evaluate the ability of COSMO-2 to represent the local meteorology at the four measurement sites, we interpolated COSMO-2 analysis fields horizontally to each site and vertically to 18 altitude levels between 10 and 3240 m above model ground. This allows us to compare COSMO-2 with meteorological measurements at different heights above ground. Furthermore, it allows assessing the effect of a mismatch between the true altitude of a site and its representation in the model where the topography is smoothed due to the limited model resolution. Although the gentle hill at Beromünster and the flat area around Gimmiz are well represented, the model’s elevation at the mountain sites Früebüel and Lägern-Hochwacht are 169 and 274 m, respectively, lower than the true elevation. Therefore, we compared COSMO-2 output at two different levels, i.e., at the altitude of the measurement a.s.l. (“true”), and at the measurement height a.m.g.l. (above model ground level; “model”). The true altitudes and the corresponding model altitudes are summarized in Table 3.2.

Hourly COSMO analysis fields were used to drive offline atmospheric transport simulations with a modified version of the LPDM FLEXPART [Stohl et al., 2005]. FLEXPART simulates the transport and dispersion

\[ \text{For more details see http://cosmo-model.org/content/tasks/operational/default.htm.} \]

Table 3.2: Simulation characteristics for the four measurement sites of the CarboCount CH network. Listed from left to right are the FLEXPART-COSMO particle release heights (above model ground level), the “true” site altitudes (m a.s.l.), smoothed COSMO numerical weather prediction model’s (~4 km²) site altitude, and the geographic site locations.

<table>
<thead>
<tr>
<th>Site</th>
<th>Meas. height</th>
<th>Rel. heights</th>
<th>Alt.</th>
<th>Alt. COSMO</th>
<th>Lat., Lon.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beromünster</td>
<td>212</td>
<td>212</td>
<td>797</td>
<td>723</td>
<td>47.1896, 8.1755</td>
</tr>
<tr>
<td>Früebüel</td>
<td>5</td>
<td>50–100</td>
<td>982</td>
<td>813</td>
<td>47.1158, 8.5378</td>
</tr>
<tr>
<td>Gimmiz</td>
<td>32</td>
<td>32</td>
<td>443</td>
<td>452</td>
<td>47.0536, 7.2480</td>
</tr>
<tr>
<td>Lägern-Hochwacht</td>
<td>32</td>
<td>100–200</td>
<td>840</td>
<td>566</td>
<td>47.4822, 8.3973</td>
</tr>
</tbody>
</table>
of infinitesimally small air parcels (referred to as particles) by advective as well as turbulent and convective transport. It can be run either in forward mode (source-oriented, i.e., released from sources) or backward mode (receptor-oriented, i.e., released backward from receptors). The advective component is calculated from the 3-D wind fields provided by COSMO, and the turbulent transport is based on the scheme of Hanna [1982], which diagnoses ABL and turbulence profiles for stable, neutral and unstable boundary layers based on the Monin–Obukhov similarity theory. FLEXPART was modified to run directly on the native grid of COSMO, which is a rotated longitude–latitude grid on a hybrid geometric (i.e., fixed in space) vertical coordinate system. The fact that the original FLEXPART model already operates on a fixed-in-space co-ordinate system greatly facilitated the adaptation to COSMO. In order to be as compatible as possible with the driving NWP (Numerical Weather Prediction) model, the same version of the Tiedtke sub-grid convection scheme [Tiedtke, 1989] as used in COSMO-7 was implemented in FLEXPART-COSMO, replacing the standard Emanuel convection scheme [Forster et al., 2007]. Convection is treated as a grid-scale process in COSMO-2 and, hence, no sub-grid convection parameterization is run in either COSMO or FLEXPART-COSMO for the 2 km × 2 km domain. From all four sites, backward transport simulations with FLEXPART-COSMO were started every 3 h to trace the origin of the observed air parcels. In each simulation, 50 000 particles were released from the site’s position at site-dependent heights above ground and traced backward in time over 4 days or until they left the simulation domain. The simulations were performed in a nested configuration with COSMO-2 providing the meteorological inputs for the inner domain and COSMO-7 for the outer domain once the particles left the COSMO-2 region. Simulated residence times \( \tau \) (s m\(^3\) kg\(^{-1}\)) described in Sect. 3.3.4 were generated for two separate output domains: a high-resolution grid over Switzerland at 0.02° × 0.015° horizontal resolution extending from 4.97 to 11.05° E and 45.4875 to 48.5475° N, and a coarser European grid at 0.16° × 0.12° resolution extending from −11.92 to 21.04° E and 36.06 to 57.42° N. Due to the relatively well-represented topography at Beromünster and Gimmiiz, we chose to release particles at the measurement height above model ground level. The relatively poor representation of topography around Früebüel and Lägern-Hochwacht, however, led us to release particles from a layer between “true” and “model” height rather than from a single height. The particle release heights were chosen based on meteorological evaluation of COSMO presented below and are listed in Table 3.2.

### 3.3.3 Land cover data set

In order to evaluate the sensitivity of the measurement sites to different land cover types (LCTs), a data set of fractional land cover was produced for the FLEXPART-COSMO output domains. The land cover data set consists of LCTs classified according to the land-unit/plant functional type approach used in the land surface model CLM4 [Bonan et al., 2002b, a; Lawrence et al., 2011]. Two same calibration scales

### 3.3.4 Regional surface influence metrics

We define surface sensitivity \( \tau_{100} \) (s m\(^3\) kg\(^{-1}\)) as the residence time of the particles in a 100 m thick layer above model ground divided by the density of dry air in that layer. A layer thickness of 100 m was selected as a compromise between the requirement of selecting a height low enough to be always located in the well-mixed part of the ABL and high enough to allow for a statistically sufficient number of particles in the layer. The results were largely insensitive to this choice as confirmed by comparing with results for \( \tau_{50} \) (50 m) and \( \tau_{200} \) (200 m). Maps of the total residence time summed over the (4-day) simulation period are commonly referred to as footprints and describe the sensitivity of a measurement site to upwind surface fluxes [Seibert and Frank, 2004]. For this study only monthly or seasonally averaged residence times were used to characterize the surface influence of the four sites and are hereafter referred to as mean surface sensitivities, \( \overline{\tau} \). Hereafter temporally averaged quantities also have an overline.
The spatial sum of monthly mean surface sensitivities, the total surface sensitivity $T_t$, gives a direct approximation of how much the air parcels arriving at a site have been in contact with the simulation domain’s surface during the simulation period and is defined as

$$T_t = \sum_{i,j} \tau_{i,j}, \quad (3.3.1)$$

where $i$ and $j$ are spatial indices.

Short-term variations in observed trace gas concentrations are mainly determined by upwind surface fluxes, which vary with the associated land cover type. In order to investigate the influence of different LCTs on each measurement site, monthly LCT contributions ($C_{\text{LCT}}$) were calculated as the weighted mean of LCT fractions $f_{\text{LCT},i,j}$ over the FLEXPART output grid, using monthly mean surface sensitivities $\tau_{i,j}$ as weights (Eq. 3.3.2). With equal surface flux strengths, each LCT would contribute the respective fraction $C_{\text{LCT}}$ of the observed signal.

$$C_{\text{LCT}} = \frac{1}{T_t} \sum_{i,j} \tau_{i,j} \cdot f_{\text{LCT},i,j} \quad (3.3.2)$$

In order to better gauge the decrease of surface sensitivity with increasing distance, we define the radial surface sensitivity $T_k$ for a site as

$$T_k = \frac{1}{\Delta d} \sum_{i,j} \tau_{i,j} \quad \forall i,j : \quad d_k < d_{i,j} < d_k + \Delta d, \quad (3.3.3)$$

where $d_{i,j}$ is the great-circle distance of the grid cell with indices $i$ and $j$ from the measurement’s site position, and index $k$ defines a discrete distance bin of width $\Delta d$.

In order to compare the area of surface influence of each site, we investigated cumulative surface sensitivities defined as

$$s(\tau) = \sum_{i,j} \tau_{i,j} \quad \forall i,j : \quad \tau_{i,j} > \tau. \quad (3.3.4)$$

The area of surface influence is then defined as the region surrounding the site bounded by the isoline $\tau_{s50}$, at which the cumulated surface sensitivity includes 50% of the total surface sensitivity:

$$\tau_{s50} : s(\tau_{s50}) = 0.5T_t. \quad (3.3.5)$$

Similar metrics were computed by Gloor et al. [2001] using trajectory simulations. They derived a concentration footprint from the decay of the correlation between population density, integrated along the trajectories, and C₂Cl₄ measurements with increasing distance from the measurement site. Although they showed the robustness of their methods, we argue that the independence of $T_k$ and $\tau_{s50}$ from trace gas measurements and associated surface fluxes constitutes an improvement of the definition of the concentration footprint. Furthermore, the application of an LPDM model that better describes atmospheric transport and dispersion constitutes a clear improvement over their approach but comes at much higher computational cost.
3.4 Results and discussion

3.4.1 Local site characteristics

The Beromünster site is a 212 m tall, decommissioned radio tower located on a gentle hill in an agricultural area in central Switzerland with an elevation of 797 m a.s.l. at the base (Fig. 3.2). Several small farms are located in the vicinity of the tower, and the town of Beromünster (< 7000 inhabitants) is approximately 2 km to the north. The adjacent valley bottoms are at an elevation of approximately 500 and 650 m a.s.l. Beromünster’s surroundings consist of a mosaic of agricultural uses: crops, managed grasslands, and a forested area towards the south.

The 32 m tall water tower near Gimmiz is the westernmost site of the network and is located in the flat Seeland region, a former wetland area which was converted to agricultural land in the nineteenth century (Fig. 3.2). The town of Aarberg (< 5000 inhabitants) is at a distance of approximately 2 km to the southwest and a farm is situated 200 m to the northeast. The flat area around Gimmiz mainly consists of agricultural plots of seasonal crops, known as the “vegetable garden” of Switzerland. Furthermore, the area directly surrounding Gimmiz is under groundwater protection and further surroundings are under water protection, which means that cattle grazing and use of fertilizer is tightly regulated or forbidden.

About 30 km to the southeast of Beromünster, Fruebuehl, a Swiss FluxNet site [Zeeman et al., 2010], is located
at an altitude of 987 m a.s.l. on the flank of the gently sloping prealpine Zugerberg, some 500 m above the valley floor (Fig. 3.3). The region consists of glacial lakes, managed forests and seasonal pastures. The city of Zug 10 km to the north and the small town of Walchwil 2 km to the southwest are the major nearby anthropogenic sources. A small farm is located approximately 300 m to the south. Seasonal pasture surrounds the site, and approximately 50 m to the west there is a small patch of forest, the canopy of which is higher than the measurement inlet at 4 m a.g.l. The site Längern-Hochwacht, a 32 m tall tower, is located on the east–west oriented mountain ridge Längern, at an altitude of 840 m a.s.l., and is north of the city of Zurich in the most industrialized and densely settled area of Switzerland (Fig. 3.3). The terrain falls off steeply to the north and south from the site, and the Längern crest extends about 10 km westwards at a similar altitude. Längern-Hochwacht is surrounded by deciduous and coniferous forest with a maximal canopy height of 20 m.

### 3.4.1.1 Model topography and land cover

Although the main topographic features of Switzerland are represented, the spatial resolution of 2 km creates large differences between true and model topography at the two mountain sites Früebüel and Längern-Hochwacht (see Table 3.1 and Fig. 3.3, second column). In the model topography, the general shape of the Zugerberg remains, but the site’s altitude is much lower (169 m). The steep Längern crest is not identifiable in the model topography; therefore, the site’s model altitude is much lower (274 m). On the other hand, Beromünster’s altitude is slightly lower in the model topography (74 m), but the local topographical features remain identifiable. Furthermore, the plain topography surrounding Gimmiz compares well with the model
topography and the site’s model altitude is slightly higher (9 m).

The land cover in Switzerland is highly fragmented at scales smaller than 2 km (Figs. 3.2, 3.3, third column). The actual variety of land cover, specifically plant functional types, is usually highly simplified in land surface models. Groenendijk et al. [2011] concluded that this simplification may have significant consequences for regional carbon flux modeling, especially in highly heterogeneous landscapes, such as Switzerland. Therefore, the influence of local fluxes on measured concentrations will still likely be difficult to simulate even at this relatively high resolution.

3.4.2 Local meteorology and diurnal cycle

The measured wind roses indicate frequent air flow channeling between the Jura mountain range and the Alps, resulting in either southwesterly or northeasterly wind directions (Fig. 3.4). Früebüel is an exception, where the local environment likely redirects prevailing winds. Due to its high measurement altitude (the highest), Beromünster observed the highest wind speeds. At Gimmiz, lower wind speeds due to lower measurement altitude and high frequency of northeasterly winds, colloquially known as “Bise”, are measured. Früebüel occasionally observes strong winds from southeasterly directions during foehn events [Bamberger et al., 2016]. Similar to Beromünster, Lägener-Hochwacht observed high wind speeds, which were highly channeled from either the northeast or southwest.

At Beromünster, the diurnal cycles of measured wind speed show higher values during nighttime than daytime, indicating presence in the mixed layer during daytime and transition to the nocturnal residual layer during nighttime (Figs. 3.5, 3.6). In summer, specific humidity exhibits an increase between 07:00 and 10:00 UTC (08:00–11:00 LT) and a simultaneous decrease in wind speed, which likely occurs as the expanding mixed layer gradually ascends past the tower top. The peak of specific humidity corresponds temporally to that of summertime regional methane signals (ΔCH$_4$), further indicating mixed layer influence. Summertime regional CO$_2$ signals (ΔCO$_2$) show only a small diurnal (±4 ppmv) variability, which corresponds to the expectation of a weak signal from diurnal surface flux variations at the top of a tall tower [Andrews et al., 2014]. Wintertime diurnal variability is hardly discernible in both CO$_2$ and CH$_4$ concentrations, indicating a weak influence of ABL dynamics.

At Gimmiz, the increase in wind speed during the day and decrease during the night indicates the constant presence of the measurement inlet in the surface layer, contrary to Beromünster (Figs. 3.5, 3.6). In summer and winter, CO$_2$ and CH$_4$ are negatively correlated with wind speed, further emphasizing the influence of diurnal ABL dynamics. The nighttime increase of more than 60 ppmv suggests rapid accumulation of ΔCO$_2$ in the shallow nocturnal boundary layer, and although nocturnal regional advection of ΔCO$_2$ may also contribute to the nighttime enrichment [Eugster and Siegrist, 2000], low wind speeds at night suggest that the surface influence is limited to a few tens of kilometers from the site. Both the high wintertime CO$_2$ concentrations (30 ppmv above background) and the high correlation between wintertime ΔCH$_4$ and ΔCO$_2$ indicate that wintertime diurnal ABL dynamics are responsible for observed diurnal variability. Please note that the winter was atypically mild [2.3°C above the norm from 1961 to 1990; MeteoSwiss, 2014] for regions north of the Alpine divide, which would have caused increased wintertime respiration, and contributed to the high observed CO$_2$ concentrations.

At Früebüel, the large magnitude in the temperature’s daily cycle, the low measured wind speeds, and the high humidity indicate a strong surface influence (Figs. 3.7, 3.8) and is consistent with the near-surface measurement height. During summer, CO$_2$ concentrations decreased in the morning along with an increase in temperature and humidity, both before wind speed increased. This typifies the influence of photosynthetic activity and further indicates a strong local surface influence.

The second mountaintop site Lägener-Hochwacht shows a similar behavior to Beromünster with a delayed
Figure 3.4: Wind roses at the four measurement sites during the study period (1 March 2013–28 February 2014) for observed (first column) and simulated horizontal wind at two different model heights: at the height of the measurement a.m.g.l. (Model, second column), and at the true height of the measurement a.s.l. (True, third column). The wind roses display the wind speed probability distribution split into incident 30° wind direction bins. Wind from the north is upward and circular lines demarcate graduating 5th percentiles. Labels above each panel show the height above ground for the measurements (first column) and height above the COSMO-2 model ground for the simulated data (second and third columns).

increase in daytime temperatures and higher wind speeds at night than during the day (Figs. 3.7, 3.8). Especially during summer, the diurnal cycles of measured wind speed show higher values during nighttime than daytime, which indicates a shift from the mixed layer during daytime to the residual layer during nighttime, and an increased influence of nocturnal jets. Specific humidity exhibits an increase between 06:00 and 09:00 UTC (07:00–10:00 LT) and a simultaneous decrease in wind speed, further indicating a shift to the mixed layer. The delay in the decrease of ∆CO₂ and peak of ∆CH₄ at 09:00 UTC indicate upward mixing of air containing nocturnally accumulated CO₂ and CH₄, which we also observe at Beromünster.
3.4. Results and discussion

On average, the mixed layer begins to influence Längern-Hochwacht measurements an hour earlier than at Beromünster. During winter, the additional 5 ppmv offset above that of Früebüel in the flat diurnal cycle of $\Delta CO_2$ and $\Delta CH_4$ concentrations indicates nearby anthropogenic sources and weak influence from ABL dynamics, respectively.

3.4.2.1 COSMO-2 meteorology evaluation

Beromünster’s simulated wind roses compare well with the observed wind roses, but high wind speeds are simulated too frequently (Fig. 3.4). Simulated and measured diurnal cycles agree well in all seasons, and simulations at the measurement height above model ground level at 212 m agree slightly better (Figs. 3.5, 3.6). Small differences from the measurements include an overestimation of wind speeds in the afternoon in summer and a delayed and too small increase in temperature during winter.

At Früebüel, neither the dominating wind directions nor the wind speeds are well reproduced by the COSMO-2 model, suggesting strong localized influences on wind patterns. The lowest model output level (10 m a.g.l.) compares best with the near-surface meteorological characteristics of Früebüel. Because the model is evaluated at the center of the lowest model layer at about 10 m a.g.l. and the meteorological measurements are closer to the surface at 2 m a.g.l., a general overestimation of wind speeds is expected. The timing of simulated and measured diurnal variations of humidity and wind speed correspond, but humidity is biased low and wind speed is biased high throughout the day. Furthermore, the amplitude of the daily temperature cycle is underestimated, most notably in winter. On the other hand, simulated wintertime temperatures show a warm bias even at the true station height, well above the surface.

At Gimmiz, the simulated wind roses compare well, but a small bias in the northeastern wind direction exists. The diurnal cycle simulations agree well with the measurements in summer and winter. However, simulated nighttime temperature and wind speed are overestimated, suggesting an unrealistically well-mixed nighttime ABL, which in an inverse modeling framework would likely lead to an overestimation of nighttime respiration, due to an overly diluted trace gas signal.

In the highly smoothed model topography, Längern-Hochwacht is more similar to Beromünster (compare cyan lines in Figs. 3.2b and 3.3b). Therefore, the rotation to a more north–southerly axis of observed winds is most likely a local topographic effect exerted by the east–west oriented ridge on the prevailing southwesterly and northeasterly winds. The simulated wintertime temperature is too high on average at all heights shown, similar to Früebüel. The measured meteorology is usually bracketed by the simulations evaluated at 32 m a.m.g.l. and at the true height (306 m a.m.g.l.), indicating that the site would be represented best by an intermediate simulation height.

Where the “model” and “true” topography are similar, simulated and measured meteorology show good agreement for Beromünster and Gimmiz. Contrastingly, local meteorology is not reproduced accurately at the mountaintop sites due likely to the smoothed model topography. The relatively poor meteorology simulations could cause problems with simulating trace gas observations if either the influence of local sources and sinks near the site were important and not well represented or if the local topography or meteorology induces vertical transport that the transport model misrepresents.

At Beromünster and Gimmiz, where “true” and “model” topography differs little, measurements and simulations agree best at the measurement height above model ground level. For Früebüel and Längern-Hochwacht, the optimal simulation height above model ground, according to the meteorology evaluation, appears to be between the “model” measurement height and the “true” measurement height.
Figure 3.5: Mean summer (June–August 2013) diurnal cycle of measured and simulated local meteorology at the sites Beromünster and Gimmiz: (a and b) temperature, (c and d) specific humidity (Sp. Hum.), and (e and f) wind speed (W. S.). Also shown are mean diurnal cycles of measured (g and h) regional CO$_2$ signals ($\Delta$CO$_2$), and (i and j) regional CH$_4$ signals (ΔCH$_4$). The measurement and simulation heights above ground are listed in the figure legends. Simulated meteorology is shown for two different heights, the height of the measurement a.m.g.l. (Model, dark blue), and the simulation height a.m.g.l., which corresponds to the “true” measurement altitude a.s.l. (True, light blue). The time zone in Switzerland is central European time (CET or UTC + 1).

### 3.4.3 Regional surface influence

#### 3.4.3.1 Measured regional signals

Over the Swiss Plateau, daytime monthly averaged regional CO$_2$ signals ($\Delta$CO$_2$) vary from −5 ppmv during warm summer days to +15 ppmv during cold winter days (Fig. 3.9a, b). During the warmer months, at daytime, intense vertical mixing caused regional CO$_2$ signals to be similar across sites. During the months of May and November, stormy weather reduced diurnal variation and the differences in regional signals between sites.

With a similar temporal pattern to CO$_2$ regional signals, daytime monthly averaged regional CH$_4$ signals (ΔCH$_4$) vary from +0.05 ppmv (+50 ppbv) during warm summer days to +0.1 ppmv (+100 ppbv) during cold winter days (Fig. 3.9c, d). Due to the same meteorological conditions conducive to vertical mixing during summer days and the months of May and November, regional CH$_4$ signals are similar across the measurement network.
3.4. Results and discussion

![Graph showing temperature, specific humidity, wind speed, CO₂ concentration, and CH₄ concentration over the hour of day (UTC) for Beromünster and Gimmiz.]

Figure 3.6: Similar to Fig. 3.5, the mean diurnal cycles during winter (December 2013–February 2014) at the sites Beromünster and Gimmiz.

On the other hand, the atmospheric stratification that accompanies reduced solar heating caused regional signals to differ more between measurement sites during nighttime and winter. For example, the cold and fair weather during December and associated high atmospheric stratification reduced diurnal variation and increased the differences between sites. Furthermore, due to a combination of site characteristics and atmospheric stratification, regional signals differed most between Beromünster and Gimmiz.

The small diurnal variation of observed regional CO₂ and CH₄ signals at Beromünster is expected, being vertically distant enough from the surrounding land surface to rarely observe nocturnal respiration fluxes. This damped signal contrasts that of the other sites and is often similar to the daytime measurement values of other sites. Interestingly, summer nighttime measurements are similar to the background estimate. Also, the higher daytime regional CH₄ signals during summertime coincide with the location in an area of very high cattle density [Hiller et al., 2014]. During winter, relatively low CO₂ measurements indicate minimal anthropogenic influence.

The large diurnal variation in both of the observed regional signals at Gimmiz is difficult to understand. The strong CO₂ signals are likely related to the combination of fluxes from nearby settlements and crops and a stable nocturnal boundary layer. The summertime peak in nighttime regional signals points toward a biogenic cause. Both the high water table and the practice of till farming may also contribute to the biogenic CO₂ fluxes, and the high water table would aid in understanding the strong CH₄ signals. Again, the strong nighttime regional signals may also be due to nocturnal regional advection of CO₂ [Eugster and Siegrist, 2000], although low wind speeds do not support this hypothesis.
At Früebüel, local topography is not conducive to a stable nocturnal surface layer and therefore the nighttime regional CO$_2$ signals are likely not as high as would be expected in flat terrain. The summertime peak in nighttime regional CO$_2$ signals is not as intense as that of Gimmiz but shows similar annual variation, pointing towards respiration fluxes. As at Beromünster, relatively low wintertime CO$_2$ measurements indicate minimal anthropogenic influence. The higher daytime regional CH$_4$ signals during summertime coincide with the location in an area of high cattle density, also similar to Beromünster.

At Lägern-Hochwacht, the observed diurnal variation of regional CO$_2$ signals is small, similar to Beromünster (Fig. 3.9). During winter, the elevated day- and nighttime regional signals indicate a strong anthropogenic influence, which corresponds with the surrounding industrialized area.

### 3.4.3.2 Simulated surface influence

The monthly total surface sensitivities ($\overline{T_f}$) differ most between sites during periods of higher atmospheric stratification (Fig. 3.9e, f), which is mainly due to the difference between particle release altitude at the site and average altitude of the surrounding (< 500 km) land surfaces. Therefore, the difference between Beromünster and Gimmiz is greatest and results from their locations on a tall tower on top of a hill or on a flat plain on a small tower with associated particle release altitudes at 1014 and 485 m a.s.l., respectively. In short, air parcels arriving at Gimmiz had the most contact with the land surface, whereas air parcels arriving at Beromünster had the least contact with the land surface.
3.4. Results and discussion

Figure 3.8: Similar to Fig. 3.5, mean diurnal cycles during winter (December 2013–February 2014) at the sites Früebüel and Lägern-Hochwacht. The Früebüel meteorological measurements were made at 2 m a.g.l.

The annual variation of the total surface sensitivities is very similar to the observed regional greenhouse gas signals, which indicates qualitative success in simulating surface sensitivity (Fig. 3.9). For example, during the warmer months, at daytime, increased vertical mixing causes total surface sensitivities to be similar across sites. During the months of May and November, stormy weather also reduced differences between sites. Total surface sensitivity differences between measurement sites increased during nighttime and winter, similar to the regional signals. Again, the cold and clear weather during December and associated high air mass stratification reduced diurnal variation and increased the differences between sites. That is, for the same reasons we qualitatively understand annual and diurnal variation in regional signals, we can understand variation in total surface sensitivity.

Potential monthly LCT contributions, $C_{LCT}$, vary little throughout the year and on average reflect the typical land cover for Switzerland and central Europe (Fig. 3.10). At all sites, the arriving air parcels spent about $\sim 30\%$ directly above forest LCTs and about $\sim 50-60\%$ of the time above crop and grassland LCTs combined. For example, in Fig. 3.10a, air parcels, which were observed during the month of March 2013 at Beromünster and were in contact with the surface (< 100 m.a.m.g.l.), spent approximately 20% of the time over the evergreen forest LCT, 10% of the time over the deciduous forest LCT, 20% over the grassland LCT, and 30% over the crop LCT.

Given the contrasting meteorological conditions of night and day, and winter and summer, mean surface sensitivity generally decreased with increasing distance from the sites (Fig. 3.11), as expected. The average distance at which 50% of the total sensitivity had accumulated is between 50 km (summer nighttime and
Figure 3.9: Monthly (YYYYMM) mean nighttime (00:00–03:00 UTC; a, c, and e) and daytime (12:00–15:00 UTC; b, d, and f) measured regional carbon dioxide signals, $\Delta CO_2$, measured regional methane signals, $\Delta CH_4$, and simulated monthly total surface sensitivities, $T_t$ (Eq. 3.3.1), during the study’s time period (1 March 2013–28 February 2014). Regional signals are computed as the measured concentration minus a background concentration estimate from Jungfraujoch, and total surface sensitivities provide a linear estimate of how much arriving air parcels at a measurement site have been in contact with the model domain’s surface.

The areas of surface influence exhibit much geographic overlap during periods of increased vertical mixing, during summer days, and are smaller and overlap less during periods of decreased vertical mixing, at night and during winter (Fig. 3.12). In the summer afternoon, all sites exhibit a similar area of surface influence due to the rapid vertical mixing in the mixed layer. The northeast–southwest orientation of the areas of surface influence is consistent with observed air flow channeling between the Jura mountain range and the Alps (Fig. 3.4). Abnormally frequent southerly winds during January and February 2014 caused areas of surface influence to be pronounced towards the south during the winter.

When considering the area of surface influence or the distance-dependent decay of surface sensitivity during
3.4. Results and discussion

Figure 3.10: Monthly (YYYYMM) land cover type (LCT) contributions $C_{LCT}$ (Eq. 3.3.2) for Beromünster (a), Früebüel (b), Gimmiz (c), and Lägern-Hochwacht (d), calculated as the pixel-wise multiplication of the monthly mean surface sensitivities with the respective LCT fraction and divided by the monthly averaged total surface sensitivities.

periods of higher atmospheric stratification, Gimmiz and Früebüel are similar and Beromünster and Lägern-Hochwacht are also similar. This shows the effect of presence within the surface layer on surface sensitivity. That is, presence within the surface layer usually results in a sharp decrease of surface sensitivity with distance and a correspondingly small area of surface influence as seen at Gimmiz and Früebüel. Contrastingly, the location above the surface layer during periods of higher atmospheric stratification results in an initial increase of surface sensitivity with distance before decreasing, and results in a relatively large area of surface influence as seen at Beromünster and Lägern-Hochwacht at nighttime and during winter.

Beromünster exhibits the lowest total surface sensitivity of the sites (Fig. 3.9), and surface sensitivity initially increases before decreasing (except summer afternoon) as distance from the measurement site position increases (Fig. 3.11). Here, we find the conceptual understanding of the exponential decay of surface sensitivity with increasing distance from a tall tower site, as presented by Gloor et al. [2001], to be valid only during well mixed conditions (Fig. 3.11c). The area of surface influence is the largest of all sites on average (Fig. 3.12), as expected. Beromünster exhibits high sensitivity to grasslands, which, along with being located in an intense dairy farming area [Hiller et al., 2014], would potentially increase influence of agricultural methane emissions. The LCTs observed at Beromünster represent typical land cover for Switzerland.

Gimmiz exhibits a high total surface influence (Fig. 3.9) that decreases sharply with increasing distance from the site (Fig. 3.11). The area of surface influence for Gimmiz covers the Seeland on average (Fig. 3.12). Opposite to Beromünster, the cold and clear weather during December caused increased coupling to the nearby...
surface (< 50 km, Fig. 3.11) and higher total surface sensitivity (Fig. 3.9), which corresponds to the small wintertime area of surface influence (Fig. 3.12). Gimmiz exhibits a high sensitivity to crop LCTs (Fig. 3.10), which is due to pronounced near-field surface sensitivity (especially in December) and the intense agricultural activity typical of the Seeland region. Qualitative understanding of the observed higher wintertime CO₂ at Gimmiz (Fig. 3.9) is aided by the higher surface sensitivity to urban areas (Fig. 3.10).

Früebüel exhibits an area of surface influence pronounced to the south, covering the immediate prealpine area well (Fig. 3.12). Due to the frequent presence in the surface layer, the surface sensitivity decreases quickly with increasing distance (Fig. 3.11). Total surface sensitivity at Früebüel during wintertime is relatively small (Fig. 3.9). This is likely due to the higher particle release altitude (853–913 m a.s.l.) and the corresponding vertical distance from the average altitude of the Swiss Plateau (∼ 450 m a.s.l.). Similar to Beromünster, Früebüel exhibits high sensitivity to grasslands (Fig. 3.10) and therefore the influence of methane emissions may be increased [Hiller et al., 2014]. Früebüel shows the highest sensitivity to “bare”, Alpine areas and “freshwater areas” due to the proximity to the Alps, and the many nearby prealpine lakes.

The surface sensitivity as a function of distance (Fig. 3.11) and area of surface influence (Fig. 3.12) of
Figure 3.12: Area of surface influence (Eq. 3.3.5) defined as the isoline at the site-dependent value \( \tau_{50} \) encompassing 50\% of the total mean surface sensitivities. Lines are color coded according to measurement site – Beromünster: dark blue, Früebüel: orange, Gimmiz: light blue, Lägern-Hochwacht: red. (a) Summer (June–August, 2013), (b) winter (December 2013–February 2014), and (c) and (d) summer (June–August 2013) in the afternoon (15:00 UTC) and at nighttime (03:00 UTC), respectively. Local time is central European time (CET or UTC +1).

Lägern-Hochwacht show similarity to those of Beromünster. Total surface sensitivities are greater than those of Beromünster but less than those of the other sites (Fig. 3.9), which the relatively large areas of surface influence also indicate. The comparably high sensitivity to distant surfaces is due to the elevated release height and small vertical distance from surrounding land surfaces. The particle release altitudes are lower (666–766 m a.s.l.) than Beromünster or Früebüel and thereby vertically closer to the average Swiss Plateau altitude (∼450 m a.s.l.). This results in relatively higher total surface sensitivity during periods of increased atmospheric stratification (Fig. 3.9), which, with the increased sensitivity to urban areas (Fig. 3.10), help to qualitatively explain comparably high observed wintertime CO\(_2\) concentrations.

The four measurement sites of the CarboCount CH network provide complementary data sets to constrain emissions from the Swiss Plateau but would not be useful for constraining emissions south of the Alpine divide, for example. At Gimmiz and Früebüel, the local environment exerts much influence, causing strong local signals to dominate the time series. Therefore, a measurement data filter to remove the strong local signal will be necessary for the Früebüel measurements and likely for the Gimmiz measurements. On the other
hand, the local environment (< 10 km) exerts little influence on the measurements made at Beromünster and Lägern-Hochwacht, where mainly regional-scale signals are observed.

Measurement sites in complex terrain still present formidable challenges for numerical weather prediction and thereby atmospheric transport modeling. The differences we found between simulated and measured local meteorology are likely due to differences between true and model topography. The ability to simulate local meteorology likely translates into the ability to accurately simulate local surface influence, which is an important aspect to simulate due to the potentially large contribution of local surface fluxes to observed greenhouse gas concentration variation, such as at the sites Früebüel and Gimmiz. Furthermore, the requirements for the spatial density and infrastructure of the measurement network are driven by periods of high atmospheric stratification and by local wind patterns. For example, due to the likely constant presence in the surface layer and resulting highly variable area of surface influence, the time series from Gimmiz is mainly useful for constraining Swiss Plateau emissions during warm days, although the tower is the same height as the tower at Lägern-Hochwacht. We recommend similar meteorological model evaluation and regional influence studies when making preliminary considerations about measurement network design and deployment.

Land cover and vegetation types influencing arriving air parcel concentrations vary little throughout the year and differences between sites are due to proximal (< 50 km) land cover. Nonetheless, the observed greenhouse gas concentrations differ substantially between sites. Thus, the collected information-rich data sets present a formidable challenge for terrestrial carbon flux modelers.

Acknowledgements

This study was funded by the Swiss National Funds (SNF) as part of the “CarboCount CH” Sinergia Project (grant CRSII2_136273). We acknowledge the use of the Jungfraujoch trace gas measurements carried out by Martin Steinbacher, Empa, in the framework of the Integrated Carbon Observation System in Switzerland (ICOS-CH), SNF grant 20FI21_1489921. We also acknowledge MeteoSwiss for the provision of their operational COSMO analysis products and of the meteorological measurements at Lägern-Hochwacht. Swiss Fluxnet is acknowledged for the meteorological measurements at Früebüel. We thank Tesfaye Berhanu and Lukas Emmenegger for reading draft versions and giving helpful comments. We also acknowledge the R Core Team [2014] for their hard work maintaining and developing the R software (version 3.1.0). Edited by: C. Gerbig
Chapter 4

A CO-based method to determine the regional biospheric signal in atmospheric CO₂

Manuscript submitted to Tellus B

Authors: Brian Oney¹, ², Nicolas Gruber², ³, Stephan Henne¹, Markus Leuenberger⁴, Dominik Brunner¹, ²

¹ Lab. for Air Pollution/Environmental Technology, Dübendorf, Switzerland
² ETH Zurich, Center for Climate Systems Modeling, Zurich, Switzerland
³ ETH Zurich, Inst. of Biogeochemistry and Pollutant Dynamics, Zurich, Switzerland
⁴ Univ. of Bern, Physics Inst., Climate and Environmental Division, and Oeschger Centre for Climate Change Research, Bern, Switzerland

NOTE: The Beromünster site abbreviation BEO has been changed to BRM and the Lägern-Hochwacht site abbreviation LAE has been changed to LHW, and are thus different from the previous Chapter.
4.1 Abstract

Regional-scale inverse modeling of atmospheric carbon dioxide (CO$_2$) holds promise to determine the net CO$_2$ fluxes between the land biosphere and the atmosphere. This approach requires not only high fidelity of atmospheric transport and mixing, but also an accurate estimation of the contribution of the anthropogenic and background CO$_2$ signals to isolate the biospheric CO$_2$ signal from the atmospheric CO$_2$ variations. Thus, uncertainties in any of these three components directly impact the quality of the biospheric flux inversion. Here, we present and evaluate a carbon monoxide (CO)-based method to reduce these uncertainties solely on the basis of co-located observations. To this end, we use simultaneous observations of CO$_2$ and CO from a background observation site to determine the background mole fractions for both gases, and the regional anthropogenic component of CO together with an estimate of the anthropogenic CO/CO$_2$ concentration ratio to determine the anthropogenic CO$_2$ component. We apply this method to two sites of the CarboCount CH observation network in the Swiss Plateau, Beromünster and Lägern-Hochwacht, and use the high-altitude site Jungfraujoch as background for the year 2013. Since such a background site is not always available, we also explore the possibility to use observations from the sites themselves to derive the background. We contrast the method with the standard approach of isolating the biospheric CO$_2$ component by subtracting the anthropogenic and background components simulated by an atmospheric transport model. These tests reveal superior results from the observation-based method with retrieved wintertime biospheric signals being small and having little variance. Both observation- and model-based methods have difficulty to explain observations from late-winter and springtime pollution events in 2013, when anomalously cold temperatures and northeasterly winds tended to bring highly CO-enriched air masses to Switzerland. The uncertainty of anthropogenic CO/CO$_2$ emission ratios is currently the most important factor limiting the method. Further, our results highlight that care needs to be taken when the background component is determined from the site’s observations. Nonetheless found, future atmospheric carbon monitoring efforts would profit greatly from at least measuring CO alongside CO$_2$.

4.2 Introduction

The accurate determination of the net fluxes of carbon dioxide (CO$_2$) between the atmosphere and the land biosphere is a key objective for global carbon research, as it represents currently the least well-known component of the global carbon budget [Le Quéré et al., 2015]. The reasons for this limited quantitative understanding of the land biosphere fluxes are manifold, but include their high spatiotemporal variability and the complexity of the underlying processes governing these fluxes. Due to the time- and space-integrative nature of atmospheric transport and mixing, the inversion of atmospheric CO$_2$ observations has played a very important role in overcoming some of these challenges [Ciais et al., 2010a]. However, this approach hinges very sensitively on the ability of atmospheric transport models to accurately connect surface fluxes with the variability of atmospheric CO$_2$ at the observing sites [Baker et al., 2006; Gurney et al., 2003; Lin and Gerbig, 2005; Gerbig et al., 2008]. The method also requires the accurate determination of other contributions to the observed CO$_2$ variability, namely anthropogenic emissions, air-sea CO$_2$ fluxes, and CO$_2$ fluxes from other systems, such as lakes and rivers [Regnier et al., 2013]. In the most commonly chosen atmospheric CO$_2$ inversion approach, the contribution of these processes to the CO$_2$ variability at the observing sites is quantified by estimating these surface fluxes based on independent constraints, and then by using these as boundary conditions in the atmospheric transport model [Gurney et al., 2004, 2008; Peylin et al., 2013]. The biospheric signal to be inverted is then estimated after subtraction of these other components from the observed atmospheric CO$_2$, which may introduce significant uncertainties [Ballantyne et al., 2015]. Thus any bias in the estimates of the surface fluxes in these components and any error in atmospheric transport acting on these surface fluxes will cause a bias in the estimated biospheric signal, and hence a bias in the inversely
estimated net biospheric flux [Goecckede et al., 2010b].

This problem tends to become worse in regional inversions, i.e., in inversions where the optimization of the fluxes is conducted over a limited domain only [e.g. Gerbig et al., 2003b; Peylin et al., 2005]. Here, one needs to consider an additional contribution to the observed atmospheric CO$_2$ variations, namely the “background” CO$_2$ concentration that originates from outside the regional domain of interest and is then transported to the observing sites within the domain [Goecckede et al., 2010b]. In most regional inversions that focus on terrestrial systems, the air-sea CO$_2$ fluxes are negligible, so that in the context of these inversions, the observed atmospheric CO$_2$ is assumed to be driven only by anthropogenic and biospheric CO$_2$ fluxes originating from sources and sinks within the domain, and the background CO$_2$ stemming from outside the domain. In the case of regional-scale inversions, the anthropogenic and background components are usually estimated from simulations with an atmospheric transport model, and the regional biospheric component is then isolated by subtracting these components from the observations [e.g. Goecckede et al., 2010a; Broquet et al., 2011; Meesters et al., 2012]. This biospheric component can then be used to estimate the biospheric CO$_2$ fluxes by means of inverse modeling [Gerbig et al., 2003b].

The main concerns with using regional-scale atmospheric transport models to estimate the anthropogenic and background components are the combined uncertainties from the transport model, the anthropogenic emission inventory used to compute the regional anthropogenic contribution, and the background concentration field typically taken from a global or continental-scale CO$_2$ assimilation model. The relative contribution to the overall uncertainty likely varies from study to study depending on the size of the domain, the magnitude of fossil fuel emissions and the complexity of the atmospheric transport. Also, the CO$_2$ concentration fields used as boundary conditions for the nested model [e.g. Goecckede et al., 2010a; Broquet et al., 2011; Pillai et al., 2011, 2012; Meesters et al., 2012] may contain biases, which can have a large effect on the resulting inverted biospheric CO$_2$ fluxes [Peylin et al., 2005; Goecckede et al., 2010b]. A further complication in the context of regional inverse modeling is the risk to assimilate the same observations that have already been assimilated in the global model [Roedenbeck et al., 2009; Rigby et al., 2011].

Deriving background concentrations directly from the observations at a given site or a nearby background site is a common method in inverse modeling studies of halocarbons [Manning et al., 2003; Brunner et al., 2012; Hu et al., 2015], but to our knowledge, this has not yet been used in the formal inverse modeling of atmospheric CO$_2$. In order to avoid some of the pitfalls associated with the model-based estimation of the background and anthropogenic components of the measured CO$_2$ concentrations, observation-based estimates of these two components can be used.

The applicability of CO as a tracer for anthropogenic CO$_2$ emanates from both being tightly linked with combustion processes [Zondervan and Meijer, 1996; Potosnak et al., 1999; Gerbig et al., 2003b]. Anthropogenic CO is a product of incomplete combustion of carbon-based fuels and therefore the molar ratio of CO : CO$_2$ is a direct measure of the efficiency of the combustion. But CO has also other important sources such as wildfires and the atmospheric oxidation of methane and non-methane hydrocarbons (NMHC). Oxidation of methane is thought to provide a mostly uniform global background of CO of about 25 ppb [Holloway et al., 2000] and can therefore be neglected in regional-scale inversions. Duncan et al. [2007] estimate that oxidation of anthropogenic and biospheric NMHC contributes about 7% and 15% of the global CO source, respectively, the former taking place mostly in northern mid-latitudes and the latter in the tropics. This is a non-negligible contribution and thus needs to be considered together with the emissions from wildfires. CO is removed by hydroxyl oxidation to CO$_2$, and has a highly variable atmospheric lifetime (22 days in July [Miller et al., 2012] versus 254 days in January in the northern hemisphere at mid-latitudes [Sander et al., 2006]). Recognizing these challenges, CO observations provide the basis for a potentially accurate and cost-efficient method to estimate the anthropogenic contribution to the observed CO$_2$ concentrations. CO is measured not only at many air quality monitoring sites, but also increasingly at greenhouse gas observation
sites [Zellweger et al., 2012].

An alternative tracer for the anthropogenic component of atmospheric CO$_2$ is its isotopic composition, namely its $^{14}$C content. This is a well-suited and well-studied proxy of CO$_2$ produced from the burning of fossil fuel and the production of clinker (CO$_2$,FF) [Levin et al., 2003] due to the absence of $^{14}$C from fossil fuel and limestone [CaCO$_3$, Suess, 1955]. Relative to the comparatively inexpensive and simple nature of continuous CO observations, $^{14}$C observations are expensive and labor-intensive, currently preventing routine, continuous observations. The $^{14}$C observations can be further combined with the continuous CO observations in order to account for the varying ratios of fossil fuel CO$_2$ to CO [Levin and Karstens, 2007; Vogel et al., 2010; Van Der Laan et al., 2010; Vogel et al., 2013]. Furthermore, the use of $^{14}$C as an anthropogenic CO$_2$ tracer is further limited by $^{14}$C emissions from nuclear power plants [Graven and Gruber, 2011] and its inability to distinguish between CO$_2$ from biofuel burning and biospheric respiration. The relative importance of these non-fossil sources is likely to increase in the future given the general need to replace fossil fuels by renewable fuels, such as wood, biogas, and ethanol.

Despite these uncertainties, CO and $^{14}$C observation-based estimates of the fossil fuel component provide a powerful alternative to the model-based estimates. But there is one downside that applies to both CO and $^{14}$C, and that is the need to subtract the background signal, which may be obtained from simultaneously measured CO or $^{14}$C at a remote background site [Levin et al., 2003].

The determination of the background signal in atmospheric CO$_2$ from background stations has issues as well. Background observations need to be representative of the boundary of the region of interest. Even for less locally influenced sites or background sites, one needs to filter the observations for pollution and depletion events [Thoning et al., 1989]. As an alternative, some studies used GLOBALVIEW$^1$ as a source of background information [e.g. Gerbig et al., 2003b]. GLOBALVIEW is a gap-filled, meridionally averaged, and temporally smoothed data product generated from the observations of the global network of background observation sites filtered for local effects [Masarie and Tans, 1995]. GLOBALVIEW provides a useful global reference but is not necessarily a well suited estimate for a continental background needed in regional-scale modeling.

This study aims to develop and evaluate several CO-based approaches to estimate the anthropogenic and background components in atmospheric CO$_2$, from which the biospheric signal and its uncertainty can be derived. Our goal is to quantify these signals without introducing model transport and/or anthropogenic emission uncertainties. To this end we will be using co-located and nearly continuous CO and CO$_2$ observations from two sites within the CarboCount CH observation network in Switzerland [Oney et al., 2015] for the year 2013. Oney et al. [2015] showed that these site’s observations are representative of the Swiss Plateau, the most densely populated and agriculturally used region in Switzerland between the Alps in the south and the Jura mountains in the north. The plateau extends about 300 km in southwest-northeast direction and has an area of about $\sim 13,000$ km$^2$. To demonstrate the benefits of the observation-based method, it is compared with model simulations of the individual CO$_2$ components employing state-of-the-art CO$_2$ inventories of anthropogenic emissions and biosphere fluxes combined with a high-resolution Lagrangian transport model.

### 4.3 CO$_2$ data analysis framework

Following the conceptual framework for regional inversions presented by Gerbig et al. [2003b], we consider atmospheric CO$_2$ as being composed of three components, i.e., background (CO$_2$,BG), and regional anthropogenic (CO$_2$,A) and biospheric (CO$_2$,B) signals (Eq. (4.3.1)). Given observations of CO$_2$ and estimates of

$^1$http://www.esrl.noaa.gov/gmd/ccgg/globalview
CO$_2$ and CO$_2$ can be determined as the residual

\[ \text{CO}_2 = \text{CO} - \text{CO}_2 - \text{CO}_2. \]  

(4.3.1)

Similarly, we consider atmospheric CO to be composed of background and regional signals, but in contrast to CO$_2$, the regional signal is assumed to be solely anthropogenic, i.e. stemming from the burning of fuels. This simplification seems justified given that oxidation of natural NMHC’s is a source of only about 5 Tg yr$^{-1}$ of CO over Europe as compared to direct emissions of 42 Tg yr$^{-1}$ and oxidation of anthropogenic NMHC of 15 Tg yr$^{-1}$ as estimated for the year 2000 by Mézáros et al. [2005]. Oxidation of methane is expected to contribute to the CO background but not to regional enhancements. Furthermore, emissions from biomass burning can be neglected, since wildfires are rare in Switzerland and Central Europe and no major events were reported for the year 2013. Accepting this simplification, the regional anthropogenic signal CO$_A$ is given by

\[ \text{CO}_A = \text{CO} - \text{CO}_B. \]  

(4.3.2)

The anthropogenic CO$_2$ signal, i.e., CO$_2$ can then be estimated from the anthropogenic CO signal using a CO$_2$/CO apparent ratio $\beta$ (Eq. (4.3.3)), i.e. that observed at an observation site, derived from the slope of a regression between anthropogenic CO$_2$ and CO regional signals:

\[ \text{CO}_2 = \beta \times \text{CO}_A. \]  

(4.3.3)

Combining equations 4.3.1 to 4.3.2 we obtain the regional biospheric signal

\[ \text{CO}_2 = \text{CO} - \text{CO}_2 - \beta(\text{CO} - \text{CO}_B). \]  

(4.3.4)

Given co-located observations of CO and CO$_2$, a site-specific $\beta$. Eq. (4.3.4) yields biospheric CO$_2$ signals derived solely from observations. Note that the two backgrounds CO$_B$ and CO$_2$ need to be derived in a consistent way using the same method and the same observation site for both signals. However, CO$_B$, CO$_2$, and $\beta$ are dependent on choices made during derivation. Therefore, their effect on the resulting biospheric signals will be evaluated in a set of sensitivity experiments. An overview of derivation of all background and anthropogenic component variants of the observation-based approach as well as two standard model-based approaches is presented in Table 4.2. Details will be given in the following section.

### 4.4 Data and methods

#### 4.4.1 Observations

Table 4.1: Simulation characteristics for two observation sites of the CarboCount CH network. Listed from left to right are observation heights (m above ground level), FLEXPART-COSMO particle release heights (m above model ground level), the “true” site altitudes (m above sea level), smoothed COSMO numerical weather prediction model’s (∼4 km$^2$) site altitude, and the geographic site locations.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Beromünster</td>
<td>212</td>
<td>212</td>
<td>797</td>
<td>723</td>
<td>47.1896, 8.1755</td>
</tr>
<tr>
<td>Längern-Hochwacht</td>
<td>32</td>
<td>100–200</td>
<td>840</td>
<td>566</td>
<td>47.4822, 8.3973</td>
</tr>
</tbody>
</table>

CO$_2$ and CO observations for the year 2013 were taken from two sites of the CarboCount CH network.
Chapter 4. CO-derived biospheric CO$_2$-signal

[Oney et al., 2015], i.e., Beromünster (BRM) and Lägren-Hochwacht (LHW), and from the high Alpine site Jungfraujoch (JFJ) [Schibig et al., 2015]. Of the four sites of the CarboCount CH network, the two sites BRM and LHW were identified to be sensitive to surface fluxes from large parts of the Swiss Plateau [Oney et al., 2015]. BRM is a 217 m tall decommissioned radio transmission tower situated on a moderate hill at 797 m a.s.l. (above sea level) at the southern border of the central Swiss Plateau. A detailed description of the observation system at BRM is presented in Berhanu et al. [2016]. LHW is a mountain top site at 840 m a.s.l. on a steeply sloping east-west oriented crest in the northeastern part of the Swiss Plateau. JFJ is located at 3650 m a.s.l. and is mostly sampling free tropospheric air [Zellweger et al., 2003; Henne et al., 2010]. It is therefore often used to characterize background conditions over continental Europe [e.g. Levin et al., 2003; Gamnitzer et al., 2006]. All sites were equipped with PICARRO (Santa Clara, California, USA) G2401 cavity ring-down spectrometers [Crosson, 2008; Rella et al., 2013] that measure CO$_2$, methane (CH$_4$), water vapor (H$_2$O) and CO at approximately 0.5 Hz. Beromünster observations used in this study were taken from the highest of five sampling heights at 212 m, sampled four times per hour for three minutes. Lägren-Hochwacht observations were made from the tower at a height of 32 m.

CO$_2$ and CO measurements were calibrated against the corresponding international reference scales, WMO X2007 for CO$_2$ [Zhao and Tans, 2006], and WMO X2014a for CO. The calibration of target gas measurements, which are not used for the calculation of calibration coefficients, indicates an accuracy of the CO$_2$ and CO measurements of $\sim 0.07$ ppm and $\sim 4$ ppb, respectively, computed as the 10-day averaging window root mean square error (RMSE) of individual target measurements. We take this quantity as the respective uncertainty $\sigma$ of both gases. For this study, all observations were aggregated to 3-hourly averages during the one-year period of 2013-01-01 to 2013-12-31.

4.4.2 Observation-based CO$_2$ components

4.4.2.1 Background signals

In order to generate the background signals for CO and CO$_2$, i.e., CO$_2$$_{BG}$ and CO$_2$$_{BG}$, respectively, at the two observation sites Beromünster and Lägren-Hochwacht, we took the CO$_2$ and CO data from Jungfraujoch and applied the “robust estimation of baseline signal” method [REBS, Ruckstuhl et al., 2012] with a 45-day local regression window (bandwidth). The REBS method aims to preserve seasonal variability while removing short-term plume events and synoptic scale variability. Deviations from a smooth background concentration are iteratively given less weight until a robust baseline is achieved. The application of the method must account for the sources of atmospheric variability. For example, applying the REBS method to CO$_2$ must account for the possibility of both negative and positive deviations from the background concentration. For the case of CO, on the other hand, we can safely assume that regional signals will be positive.

The baseline signal for CO was obtained from the three-hourly CO observations by employing a tuning factor (b) of 3.5, a local regression window width (local neighborhood or bandwidth) of 45 days, and a maximum of 10 iterations to derive asymmetric robustness weights. The scale parameters within the respective local regression window were calculated from the below-baseline fit residuals [Ruckstuhl et al., 2012]. For CO$_2$, we used exactly the same parameters, but applied symmetric instead of asymmetric robustness weights to account for the fact that short-term deviations from the background can be either positive or negative. Also, the scale parameters within the local regression window were calculated from all fit residuals.

In order to test whether the background concentrations could also be estimated in the absence of a nearby background site such as Jungfraujoch, we also derived background concentrations directly from the observations at the target sites (BRM, LHW). The same REBS settings were applied as described above for Jungfraujoch. The smoothness of the REBS background depends on the width of the regression window and since this choice is somewhat arbitrary, we tested the sensitivity of the results to shorter (30-day) and longer
Table 4.2: An overview of the model and observation based CO$_2$ component estimates. All observation-based estimates (obs*) calculate the CO$_2$ background with a 45-day REBS, and translate CO above a similar CO background estimate with the designated $\beta$. All modeled estimates were calculated with FLEXPART-COSMO and the data product listed.

<table>
<thead>
<tr>
<th>Case</th>
<th>Background</th>
<th>Biospheric</th>
<th>Anthropogenic</th>
</tr>
</thead>
<tbody>
<tr>
<td>obs1</td>
<td>JFJ</td>
<td>Residual</td>
<td>$\beta_{\text{obs}}$</td>
</tr>
<tr>
<td>obs2</td>
<td>JFJ</td>
<td>Residual</td>
<td>$\beta_{\text{mod}}$</td>
</tr>
<tr>
<td>obs3</td>
<td>JFJ</td>
<td>Residual</td>
<td>$\beta_{\text{mod,week}}$</td>
</tr>
<tr>
<td>obs4</td>
<td>JFJ</td>
<td>Residual</td>
<td>$\beta_{\text{mod,3hr}}$</td>
</tr>
<tr>
<td>obs5</td>
<td>SITE</td>
<td>Residual</td>
<td>$\beta_{\text{obs}}$</td>
</tr>
<tr>
<td>obs6</td>
<td>SITE</td>
<td>Residual</td>
<td>$\beta_{\text{mod}}$</td>
</tr>
<tr>
<td>obs7</td>
<td>SITE</td>
<td>Residual</td>
<td>$\beta_{\text{mod,week}}$</td>
</tr>
<tr>
<td>obs8</td>
<td>SITE</td>
<td>Residual</td>
<td>$\beta_{\text{mod,3hr}}$</td>
</tr>
<tr>
<td>mod1</td>
<td>MACC</td>
<td>VPRM</td>
<td>CarboCount</td>
</tr>
<tr>
<td>mob1</td>
<td>MACC</td>
<td>Residual</td>
<td>CarboCount</td>
</tr>
</tbody>
</table>

### 4.4.2.2 Anthropogenic CO$_2$ signal

The anthropogenic CO$_2$, CO$_{2,A}$, was estimated by scaling the anthropogenic CO signal, CO$_{A}$, with the scaling factor $\beta$ (ppm CO$_2$/ppb CO; see Eq. (4.3.3)), which we derived using two different methods.

A first method was based on the observed relationship between the regional signals of CO$_2$ and CO at our CarboCount CH sites (obs1, Table 4.2). We assumed that the biospheric influence on the regional signal was negligible during wintertime (January, February, and December) and that therefore any variations in the regional signal stemmed from anthropogenic sources only, i.e., CO$_{2,A} \gg$ CO$_{2,B}$. We then estimated $\beta_{\text{obs}}$ from observed wintertime regional signals (CO$_2$-CO$_{2,\text{BG}}$ and CO$_{A}$) as the slope of a total weighted least squares regression [Krystek and Anton, 2008] forced through the origin. The regression takes into account uncertainties of both regional CO$_2$ and CO signals, and yields a single scaling factor $\beta_{\text{obs}}$ (Eq. (4.4.1)).

$$\text{CO}_2 - \text{CO}_2,\text{BG} = \beta_{\text{obs}} \times \text{CO}_A + \epsilon \quad \text{(4.4.1)}$$

where $\epsilon$ is the error term assumed to be normally distributed around zero. This assumption holds during winter when variations in both gases mainly result from similar combustion processes. Satar et al. [2016] show that this ratio varies seasonally, and approaches a value representative of the CO$_2$/CO ratio of combustion processes only during winter. Since we can only derive a meaningful $\beta$ from wintertime data, we assumed that $\beta_{\text{obs}}$ is valid for the whole study period and used it to scale all CO$_A$ to CO$_{2,A}$.

A second method relies on model simulated CO$_2$ and CO signals at the two observation sites (see Sect. 4.4.4). In this case, the total weighted least squares regression is applied to modeled regional anthropogenic CO$_{2,A}$ and CO$_A$ signals. The corresponding annual mean apparent ratio is denoted $\beta_{\text{mod}}$ and can be interpreted as an average molar ratio between CO$_2$ and CO emissions weighted by each site’s field of view or “footprint” (see Sect. 4.4.4). However, these CO$_2$/CO emission ratios vary in time and space substantially. Therefore, we also determined weekly ($\beta_{\text{mod,week}}$) and three-hourly ($\beta_{\text{mod,3hr}}$) ratios to account for variability of the ratio expected from the combined effect of the variability represented in emission inventories and the influence of variations in air mass provenance and mixing.
4.4.3 Uncertainty of the biospheric signal

Since the biospheric signal is determined by difference, its uncertainty \( \sigma_{\text{CO}_2,B} \) accumulates the uncertainty of the individual observation-based components. Assuming independence of the individual components, we can determine \( \sigma_{\text{CO}_2,B} \) by quadratically summing the uncertainty of each component of Eq. (4.3.1), i.e., the uncertainty of the background signal \( \sigma_{\text{CO}_2,\text{BG}} \), of the anthropogenic signal \( \sigma_{\text{CO}_2,\text{A}} \), and of the \( \text{CO}_2 \) observations \( \sigma_{\text{CO}_2} \):}

\[
\sigma_{\text{CO}_2,B} = \sqrt{\sigma_{\text{CO}_2}^2 + \sigma_{\text{CO}_2,\text{BG}}^2 + \sigma_{\text{CO}_2,\text{A}}^2},
\]

(4.4.2)

where the uncertainty of the anthropogenic \( \text{CO}_2 \) signal is

\[
\sigma_{\text{CO}_2,A}^2 = \beta^2(\sigma_{\text{CO}}^2 + \sigma_{\text{CO},\text{BG}}^2) + \sigma_{\beta}^2(CO - CO_{\text{BG}})^2.
\]

(4.4.3)

A constant (for the year of 2013) estimate of \( \sigma_{\text{CO}_2,\text{BG}} \) was provided by the REBS algorithm. The uncertainty of the scaling factor, i.e., \( \sigma_{\beta} \) was obtained directly as the uncertainty of the slope of the weighted total least squares regression. Finally, \( \sigma_{\text{CO}} \) was taken directly from the \( \text{CO}_2 \) observations.

4.4.4 Model simulated \( \text{CO}_2 \) components

In order to evaluate our observation-based method, the state-of-the-art Lagrangian transport model FLEXPART [Stohl et al., 2005] was employed to directly estimate each of the components of Eq. (4.3.1), with regional-scale anthropogenic and biospheric surface flux inventories, and a global model providing background \( \text{CO}_2 \) concentrations. Furthermore, in order to investigate \( \beta \), we also simulated \( \text{CO}_A \).

4.4.4.1 Atmospheric tracer transport model

The Lagrangian particle dispersion model FLEXPART [Stohl et al., 2005] that simulates the transport and dispersion of air parcels (particles) via turbulent, advective, and convective processes, was driven offline by hourly COSMO analysis fields from the operational analysis archive of MeteoSwiss. The model was run over a European domain ranging from 18.60°E to 23.21°W and 35.05°N to 57.53°N with a horizontal resolution of 0.06° × 0.06° (Figure 4.1).

FLEXPART-COSMO was run in backward mode (receptor-oriented, i.e., simulating upwind surface influence of sites) every 3 hours to simulate the movement and provenance of observed air parcels. In each simulation, 50,000 particles were released from the site’s position at site-dependent heights above ground and traced backward in time 4 days or until they left the simulation domain.

After being scaled with the dry air density \( \rho \), residence times \( \tau (\text{s m}^3 \text{kg}^{-1}) \) were recorded for a high-resolution output domain over Switzerland (4.97°E to 11.05°E and 45.49°N to 48.55°N) at 0.02° × 0.015° resolution, and a European output domain (11.92°E to 21.04°E and 36.06°N to 57.42°N) at 0.16° × 0.12° resolution. Residence times were then folded with regional surface flux inventories to arrive at dry air mole fractions [Seibert and Frank, 2004], which are estimates of respective regional signals. FLEXPART particle trajectory end points are defined by their time and position at the end of the simulation or when leaving the simulation domain. These endpoints are used to calculate initial and boundary conditions (Sect. 4.4.4.2). Further description of FLEXPART-COSMO can be found in Oney et al. [2015]. The particle release heights at the observation sites were chosen based on a meteorological evaluation of COSMO in Oney et al. [2015] and are listed in Table 4.1.
4.4. Data and methods

4.4.4.2 Lateral boundary conditions for CO$_2$

![Simulation domains of this study. The COSMO-7 represents the driving meteorology. The west European and Switzerland domains comprise the areas where surface sensitivity and flux influence is calculated for the past 4 days to simulate regional signals. Outside these temporal and spatial domains the initial concentration is taken as the background signal.](image)

The lateral boundary conditions for atmospheric CO$_2$ for the European domain were deduced from a global CO$_2$ atmospheric transport model by interpolating the 3-D CO$_2$ mole fraction fields to the 50,000 particle trajectory end points of each FLEXPART simulation and computing the average of the interpolated values. For each end point, the temporally closest 3-D model field was used for interpolation. Global CO$_2$ fields were provided by the data assimilation system of the Monitoring Atmospheric Composition and Climate (MACC) project of the European Centre for Medium Range Weather Forecast (ECMWF) [Chevallier et al., 2010; Chevallier, 2013]. We used the simulation version MACC-II/v13r1 [Chevallier, 2015] in which global surface observations including those at Jungfraujoch were assimilated, but those the CarboCount CH sites were not assimilated.
4.4.4.3 Anthropogenic CO$_2$ & CO signals

The anthropogenic emission inventories of CO$_2$ and CO were generated by merging relatively coarse global and European inventories with high-resolution inventories available for Switzerland. For CO$_2$, the global EDGAR v4.2 FT2010 “Fast Track” inventory [Olivier et al., 2011] available at 0.1° × 0.1° resolution was merged with a new high-resolution (500 m × 500 m) inventory for Switzerland developed by the company Meteotest, Switzerland, on behalf of the project CarboCount CH, hereafter referred to as the “CarboCount” inventory. The latest year available in both inventories was 2010, but the Swiss inventory was scaled to match the total for 2012 as officially reported to the United Nations Framework Convention on Climate Change [FOEN, 2014]. Both emission inventories include the emissions from the burning of fossil fuels, the burning of biomass (wood), and the production of cement.

For CO, the European TNO-MACC II emission inventory [Kuenen et al., 2014] available at approximately 7 km × 7 km resolution for the year 2009 was merged with a high-resolution (200 m × 200 m) CO inventory of Switzerland from 2005. Due to the large, mostly negative trends in European CO emissions, both inventories were scaled by nation to match officially reported values of the year 2012 (latest year available), while preserving the emission’s spatial distribution. Country totals reported to the Convention on Long-range Trans-boundary Air Pollution (LRTAP) were obtained from the EMEP/CEIP web database (http://www.ceip.at/).

As is the case for CO$_2$, the emission inventory for CO includes the burning of both fossil and modern fuels, while cement manufacturing does not lead to an emission of CO.

For both CO$_2$ and CO emissions, temporal profiles describing diurnal, day-of-week and monthly variations were prescribed based on sector-specific profiles developed in the project EURODELTA-II [Thunis et al., 2008], similar to Peylin et al. [2011]. These profiles have been developed for a source classification according to SNAP (Standardized Nomenclature for Air Pollutants) codes. However, both EDGAR and the two Swiss inventories are based on different nomenclatures, e.g., the IPCC nomenclature in case of EDGAR. Specific conversion tables were therefore developed mapping the different emission categories onto the most closely matching SNAP codes [Kuenen et al., 2014]. In addition, a country mask was applied to the EDGAR inventory, a gridded inventory without national borders, in order to apply country-specific day-of-week and monthly profiles. Diurnal profiles were identical in all countries but were adjusted to the local time in each country. Monthly scaling factors were temporally interpolated between the centers (day 15) of each month. Finally, hourly fields of total (sum over all categories) emissions of CO$_2$ and CO were reprojected to the two simulation domains, and averaged to three-hourly resolution as used by FLEXPART-COSMO. The anthropogenic CO$_2$ and CO signals were then simulated with FLEXPART-COSMO.

4.4.4.4 Biospheric CO$_2$ signal

In order to evaluate the residual regional biospheric signals inferred from the observations, we also computed this signal directly by using the net ecosystem exchange (NEE) fluxes from the Vegetation Photosynthesis and Respiration Model (VPRM) model as a boundary condition Mahadevan et al. [2008]. NEE represents the net exchange of CO$_2$ between the atmosphere and the terrestrial biosphere and in the model is equal to photosynthesis minus ecosystem respiration, since this model does not include any perturbation fluxes arising from, e.g., fires or insect outbreak. The fluxes computed by VPRM are driven by satellite and meteorology data. Parameters in VPRM controlling these fluxes had been optimized using CarboEurope-IP eddy covariance flux observations at various sites as described in Pillai et al. [2012]. After converting to a surface mass flux and reprojecting to the simulation domain, the hourly NEE fields were averaged to three-hourly resolution, and the biospheric influence on each site was then simulated with FLEXPART-COSMO.
4.5 Results & discussion

The atmospheric CO$_2$ concentrations observed at the two sites Beromünster and Lägern-Hochwacht exhibit the expected annual cycle for the northern hemisphere, with a summertime trough and a wintertime crest (Figs. 4.2 & 4.3, panel A). During the warmer months at Lägern-Hochwacht, the daily variation of CO$_2$ is due to a combination of biospheric activity and atmospheric boundary layer (ABL) dynamics [Oney et al., 2015]. Beromünster’s observations show these effects as well, but less strongly, due to a combination of
high inlet height and relatively high elevation above the Swiss Plateau owing to its location on top of a hill. Wintertime observations at Beromünster and Lägern-Hochwacht show relatively little diurnal variation, but contain samples of polluted air stretching for periods of days to weeks \cite{Oney et al., 2015; Satar et al., 2016]. Being 40.5 km apart, the two sites usually sample related air masses, resulting in similar time series. This also suggests that local influences at the two sites are small.

The modeled atmospheric CO$_2$ concentrations represent the observations well (Figs. 4.2 & 4.3, panel A), but a closer inspection reveals considerable differences in summertime and during a few individual events in winter at both sites. These differences can come from any of the three modeled components, i.e., the background, the anthropogenic, and the biospheric signals, with the biospheric signal presumably being the most uncertain.
one. Since we have derived estimates for each of these CO$_2$ components directly from co-located observations of CO$_2$ and CO (panel B–C), we can test whether this is indeed the case.

### 4.5.1 Background signals of CO$_2$ & CO

![Figure 4.4: CO$_2$ (panels A–B) & CO (panels C–D) measured concentrations (black and gray) and “robust estimate of baseline signal” (REBS) estimates (red and orange) at Beromünster, Lägern-Hochwacht, and Jungfraujoch (JFJ) during 2013. The REBS background estimates are calculated with a 45-day local regression window.](image)

Background sites such as Jungfraujoch are defined by their lack of local influence owing to them being far away from any anthropogenic emissions. Consequently, the concentration of CO is considerably lower at Jungfraujoch relative to Beromünster or Lägern-Hochwacht, where the proximity to CO sources is apparent (Fig. 4.4). Therefore, background CO signals estimated directly from Beromünster or Lägern-Hochwacht observations are typically greater than when Jungfraujoch is used as a background. Wintertime CO$_2$ background signals from Beromünster and Lägern-Hochwacht are also greater than those from Jungfraujoch owing to frequent sampling of polluted air with elevated concentrations of anthropogenic CO$_2$ at Beromünster and Lägern-Hochwacht, especially during periods of reduced vertical mixing. On the other hand, even though the air sampled at the high Alpine site Jungfraujoch exhibits little influence from Switzerland [Henne et al., 2010], summertime Jungfraujoch CO$_2$ background signals differ little from those of Beromünster or Lägern-Hochwacht. This may partly be due to a balancing of anthropogenic emissions and biospheric uptake, but is mainly due to enhanced vertical mixing.

The Jungfraujoch CO$_2$ background signal overall behaves similarly to the modeled background concentration at Beromünster or Lägern-Hochwacht, although the Jungfraujoch-based background varies much less than
Chapter 4. CO-derived biospheric CO$_2$-signal

the modeled background (Figs. 4.2 and 4.3, panel B). However, the two background signals are not strictly compatible, because they are defined differently, i.e., with regard to different spatial and temporal domains. In the case of the model-based estimate, the size and structure of the signal depends highly on the model domain, which in this case is central Europe. In contrast, the observation-based background signal from Jungfraujoch attempts to remove all recent surface influence manifested in pollution and depletion peaks even if these originated outside the model domain. This difference is defined mainly by the observations and to a lesser degree by the settings employed in the REBS method.

The large amount of variations in the model-based background suggests that our effective domain might have been too small, indicating that a backward integration time of four days is not always long enough for signatures from remote fluxes to fully dilute into the large-scale background. During these situations the air parcels likely begin and remain in the European ABL for four days time or more before reaching the observation station. This can also be seen in that the modeled CO$_2$,A and CO$_2$,BG are correlated, especially during winter when reduced vertical mixing causes CO$_2$,A emissions to accumulate in the lower troposphere. However, it should be noted that the short-term variation of model background is relatively small (< 10 ppm) compared to the anthropogenic CO$_2$ signal (< 40 ppm).

4.5.2 Anthropogenic CO$_2$ to CO ratio

The estimation of the apparent anthropogenic CO$_2$,A to COA concentration ratio, $\beta$, is one of the main challenges in the application of the CO-based method. Our standard approach was to use the slope of the wintertime relationship between the regional CO$_2$ and COA signals estimated by using Jungfraujoch as a background site. Fig. 4.5B,E reveals that these two signals are indeed highly correlated. To be consistent with previous studies, which reported the emission ratios of CO to CO$_2$, we report the ratios here as their inverse $R \equiv \beta^{-1}$. In wintertime an $R (\beta^{-1})$ of 8.39±0.14 ppb CO/ppm CO$_2$ for Beromünster and an $R$ of 7.70±0.20 for Lägern-Hochwacht was observed (see Table 4.3).

For Beromünster, Satar et al. [2016] showed that in contrast to the high CO : CO$_2$ correlation in wintertime the cross-correlations are substantially weaker during the other seasons. Also, the slopes (ratios) are different reflecting the influence of other processes driving changes in the regional signals. Springtime ratios are marked by decreasing regional CO$_2$ likely related to initial plant growth, and high COA signals are likely related to domestic heating. In summer, the correlation weakens further due to the large and highly variable contribution of the net biospheric signal (±20 ppm in regional CO$_2$) combined with weak COA signals. Observed autumn ratios reflect the weakening biopheric signals owing to smaller production and possibly increased litter decomposition combined with increasingly strong COA; i.e. they portray the gradual change from summer to winter. During winter, the correlation is strong suggesting that the biospheric influence is small and that regional CO$_2$ is driven mainly by human-induced combustion.

The extent of biospheric influence on the observed regional CO$_2$ signal becomes apparent when comparing the regional relationship $\beta$ inferred from the observations with that inferred from simulated anthropogenic signals (Fig. 4.5A,D). Here, as expected, the correlations between the simulated CO$_2$,A and COA remain strong throughout the year, as these signals are purely driven by the anthropogenic emissions of CO$_2$ and CO. The variability in the modeled relationship reflects variations in air mass origin and the corresponding influence of the spatially non-uniform CO$_2$ to CO emission ratios in Europe, as well as differences in the temporal variations of CO$_2$ and CO emissions. Although variable, these processes do not lead to substantial seasonal variations in the slope between the modeled CO$_2$,A and COA. This supports the idea that observed wintertime $\beta$ estimates appear to be representative for the entire year (Table 4.3).

Beromünster is located in a rural area where wood is frequently used for domestic heating and farm vehicle emission regulations are less strict than those for road traffic. Lägern-Hochwacht on the other hand is located
4.5. Results & discussion

Figure 4.5: Modeled and measured CO$_2$ and CO regional signals at Beromünster and Lägern-Hochwacht, colored according to season. Panel A: modeled CO$_2$ and CO at Beromünster. The slope of the regression line corresponds to $\beta_{\text{mod}}$ of method mod1. Panel B: CO$_2$ and CO regional signals above a background signal from Jungfraujoch. The slope of the regression line is calculated using only wintertime regional signals and corresponds to $\beta_{\text{obs}}$ of method obs1. Panel C: the same is shown as in panel B except using background estimates from the target site Beromünster (method obs5). Panels D-F: the same as panels A–C shown with regional signals from Lägern-Hochwacht.

Table 4.3: Sensitivity of the inverse ratios $R_{\text{obs}}$ ($\equiv \beta_{\text{obs}}^{-1}$) to the choice of observations used to determine the background signal, and to the choice of width of local regression window. Also shown are model-based ratios $R_{\text{mod}}$. The units of $R_{\text{obs}}$ are ppb CO/ppm CO$_2$. The uncertainty ($\pm$) of $R$ is determined as $2\sigma$ of the slope of the total weighted least squares regression.

<table>
<thead>
<tr>
<th>Site</th>
<th>Background</th>
<th>$R_{\text{obs}}$</th>
<th>$R_{\text{mod}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beromünster</td>
<td>JFJ, 30-day</td>
<td>8.38±0.14</td>
<td>9.53±0.14</td>
</tr>
<tr>
<td></td>
<td>JFJ, 45-day</td>
<td>8.39±0.14</td>
<td>&quot;</td>
</tr>
<tr>
<td></td>
<td>JFJ, 60-day</td>
<td>8.40±0.14</td>
<td>&quot;</td>
</tr>
<tr>
<td></td>
<td>SITE, 30-day</td>
<td>10.70±0.38</td>
<td>&quot;</td>
</tr>
<tr>
<td></td>
<td>SITE, 45-day</td>
<td>10.00±0.30</td>
<td>&quot;</td>
</tr>
<tr>
<td></td>
<td>SITE, 60-day</td>
<td>9.77±0.28</td>
<td>&quot;</td>
</tr>
<tr>
<td>Lägern-Hochwacht</td>
<td>JFJ, 30-day</td>
<td>7.67±0.19</td>
<td>8.98±0.17</td>
</tr>
<tr>
<td></td>
<td>JFJ, 45-day</td>
<td>7.70±0.20</td>
<td>&quot;</td>
</tr>
<tr>
<td></td>
<td>JFJ, 60-day</td>
<td>7.71±0.20</td>
<td>&quot;</td>
</tr>
<tr>
<td></td>
<td>SITE, 30-day</td>
<td>10.40±0.52</td>
<td>&quot;</td>
</tr>
<tr>
<td></td>
<td>SITE, 45-day</td>
<td>10.20±0.54</td>
<td>&quot;</td>
</tr>
<tr>
<td></td>
<td>SITE, 60-day</td>
<td>10.30±0.56</td>
<td>&quot;</td>
</tr>
</tbody>
</table>
Chapter 4. CO-derived biospheric CO$_2$-signal

in a relatively more densely populated and industrialized area, where combustion tends to be more efficient. The simulated apparent ratios reflect the expectation that air parcels observed at Beromünster (\(R_{mod}\) of 9.53 ± 0.14) are more CO-enriched than those at Lägern-Hochwacht (8.98 ± 0.17). Correspondingly, the observed air parcels at Beromünster tend to be more CO-enriched than those at Lägern-Hochwacht. Furthermore, seasonal variation in emission patterns and ABL dynamics has the potential to affect the apparent CO/CO$_2$ ratios. Satar et al. [2016] report significantly lower wintertime ratios for Beromünster, which is likely due to different time periods and regression approaches. They used data from two years (2013 and 2014) and applied the regression to deviations from 5-day running means. We only used data from the more polluted year 2013 and applied the regression to enhancements above the JFJ background and forced the offset to zero. Modeled ratios \(R_{mod, week}\) derived from weekly instead of annual relationships range from 7.55 to 12.60 (median of 9.35) ppb CO/ppm CO$_2$ at Beromünster, and from 6.93 to 11.20 (median of 8.79) ppb CO/ppm CO$_2$ at Lägern-Hochwacht, respectively. This variability is partly due to spatial variations of CO/CO$_2$ emission ratios and due to different temporal profiles applied to different emission sectors in the emission inventories. However, it is also partly due to significant inconsistencies between the CO and CO$_2$ inventories which are based on different spatial surrogate data. We tested the option of using EDGAR v4.2 instead of TNO-MACC II also for CO but large inconsistencies in individual grid cells were still found, for example, showing strong emissions of CO but no emissions of CO$_2$ and vice versa. Furthermore, most of the surface influence on both Beromünster and Lägern-Hochwacht is usually within distances of ≤ 300 km [Oney et al., 2015], and for Switzerland the emission inventories for CO and CO$_2$ correspond well, although also here different reference years (CO$_2$: 2010 and CO: 2005) of the inventories may lead to some spatial inconsistencies.

The observation-based ratios are relatively insensitive to the choice of the smoothing window required to determine the background signals in CO and CO$_2$ and thereby determining the remaining regional signal, but react sensitively to the choice of the background site (Table 4.3). If the site’s observations are used to determine the background signals, then the ratios increase, largely owing to the regional signal in CO$_2$ during wintertime being smaller relative to that for CO (Figure 4.4). In other words, this is caused by the SITE baseline for CO$_2$ being considerably larger than JFJ baseline for CO$_2$, whereas the CO baseline estimates remain closer together. Classically, the background signal is a matter of definition and would typically correspond to the REBS estimate from Jungfraujoch or the modeled estimate instead of REBS estimate from one of the CarboCount sites. The ratios based on regional signals relative to site-based background signals (obs5-obs8) likely correspond to more localized areas surrounding each site and are thus likely not valid for larger areas such as the Swiss Plateau. Therefore, for this application, we cannot recommend the determination of the background signals from observations, in which the local influence is large relative to the background/global variation when applying this observation-based method. By extension, we considered the ratios based on regional signals relative to site-based background signals to be of limited value for our analyses and did not pursue them further.

When comparing our results of \(R_{obs}\) with those previously reported, fossil fuel based CO$_A$/CO$_2,FF$ ratios (Table 4.4), our results are mostly smaller with the exception of two sites in coastal and remote environments. However, it needs to be emphasized that these results are not always directly comparable. First, our estimates are concentration ratios in the air, reflecting emissions and transport from a wide array of regions. Second, our anthropogenic components (CO$_2, A$ and CO$_A$) include also the contribution of the combustion of non-fossil, carbonic materials. Due to wood-burning, the use of biofuels, and waste incineration [Mohn et al., 2008], non-fossil combustion in Switzerland constitutes 14% of CO$_2$ emissions according to the Swiss national emission inventory [FOEN, 2014]. Third, owing to many technological advances since the time of the outlined studies, the combustion efficiency has increased resulting in proportionally less CO being emitted, which further reduces the ratio.
4.5. Results & discussion

Table 4.4: Summary of observed $R$'s found in previous studies. The upper portion of the table displays long-term observation results, and the lower half of the table displays observation campaign results. $CO_A/CO_2$ refers to ratios calculated from continuous $CO_2$ and CO observations above background, analogous to this study. $CO_A/CO_2, R$ refers to ratios calculated from continuous $CO_2$ and CO observations above background, analogous to this study. $CO_A/CO_2, FF$ indicates fossil fuel $CO_2$ ($CO_2, FF$) calculated from $^{14}C$ [see Levin et al., 2003]. The information used for the method is presented as the apparent ratio calculation, background, and the metric shown. The units of $R$ are ppb CO/ppm $CO_2$.

<table>
<thead>
<tr>
<th>$R_{obs}$</th>
<th>Location</th>
<th>Period</th>
<th>Method</th>
<th>Study</th>
</tr>
</thead>
<tbody>
<tr>
<td>12.4±0.5</td>
<td>Harvard forest, USA</td>
<td>1996 Winter</td>
<td>$CO_A/CO_2, A$, monthly 20th percentile, mean and standard deviation of three months</td>
<td>Potosnak et al. [1999]</td>
</tr>
<tr>
<td>12.2±0.4</td>
<td>Heidelberg urban site, Germany</td>
<td>2001-09-2004-04</td>
<td>$CO_A/CO_2, A$, Jungfraujoch $^{14}C$ &amp; GLOBALVIEW-CO, mean and standard deviation</td>
<td>Gamnitzer et al. [2006]</td>
</tr>
<tr>
<td>15.5±5.6 &amp; 14.6 ± 5.5</td>
<td>Heidelberg urban site, Germany</td>
<td>2002-2009</td>
<td>$CO_A/CO_2, A$, Jungfraujoch, weighted mean and standard deviation &amp; median and interquartile range</td>
<td>Vogel et al. [2010]</td>
</tr>
<tr>
<td>9±5</td>
<td>Lutjewad coastal site, Netherlands</td>
<td>2006-2009</td>
<td>$CO_A/CO_2, A$, Jungfraujoch, mean ± standard deviation</td>
<td>Van Der Laan et al. [2010]</td>
</tr>
<tr>
<td>11.2±9 &amp; 12.2±11 &amp; 11.9 ± 8</td>
<td>Coastal northeast USA</td>
<td>2004-2010; annual, summer, and winter</td>
<td>$CO_A/CO_2, A$: Free troposphere observations, median and uncertainty (average of uncertainty range)</td>
<td>Miller et al. [2012]</td>
</tr>
<tr>
<td>~6.8</td>
<td>Beromünster tall tower, Switzerland</td>
<td>2012-2014</td>
<td>$CO_A/CO_2, A$ (above seasonal harmonics estimates), standard major axis regression</td>
<td>Satar et al. [2016]</td>
</tr>
<tr>
<td>6.8±2.2 &amp; 11.7 ± 5.5</td>
<td>Niwot Ridge mountain site, USA &amp; 2004-01-20 &amp; 2004-03-02</td>
<td>$CO_A/CO_2, A$, average from 2003-11-2004-04 with western winds, mean and standard deviation</td>
<td>Turnbull et al. [2006]</td>
<td></td>
</tr>
<tr>
<td>11.2±2 &amp; 14 ± 2</td>
<td>Sacramento metropolitan area, USA &amp; 2009-02-27 &amp; 2009-03-06</td>
<td>$CO_A/CO_2, A$: Free troposphere observations, linear regression slope ±σ</td>
<td>Turnbull et al. [2011]</td>
<td></td>
</tr>
<tr>
<td>56 (33) &amp; 22 (20)</td>
<td>Downwind of China and Japan, respectively (outliers removed)</td>
<td>2001-02-24 to 2001-04-10</td>
<td>$CO_A/CO_2, A$, none, reduced axis regression</td>
<td>Suntharalingam [2004]</td>
</tr>
</tbody>
</table>

4.5.3 Anthropogenic $CO_2$

The anthropogenic component $CO_2, A$ estimated in our base case (i.e., ”obs1”) is a considerable component of the total $CO_2$ at the two observing sites of the CarboCount CH network (Figure 4.2 and 4.3, panels B). In the ”obs1” base case, Jungfraujoch is used as the background for both CO and $CO_2$ and $β$ is inferred from the winter-time regional signals at the respective two sites (see Table 4.2). Particularly in wintertime, the variations in $CO_2, A$ ($σ = ±9.5$ ppm) dominate the variations in atmospheric $CO_2$, explaining most of the observed variability. In summertime, the signals are substantially weaker ($σ = ±2$ ppm), largely owing to increased vertical mixing in the lower troposphere.

Our estimated $CO_2, A$ has only few negative excursions (1.6% & 0.5% of the time at Beromünster and Läger-Hochwacht, respectively), even though there was no constraint on the method to ensure the expected positive definiteness of this component. This increases the confidence in this estimate. These few negative excursion
result from the few occasions when the background CO signal from Jungfraujoch was greater than the observed CO at Beromünster or Lägern-Hochwacht. Most of these negative excursions correspond to times when also CO$_2$ at the two sites was lower than the background at Jungfraujoch. Thus, these conditions occur when the air arriving at Jungfraujoch had a different origin than that arriving at our CarboCount CH sites. The observation-based estimate of the anthropogenic CO$_2$ component also looks plausible when compared to the simulated anthropogenic signal (mod1) for the whole year 2013 (Figs. 4.2 and 4.3, panel C). In fact, the directly modeled anthropogenic signals (mod1) agree remarkably well with the estimates derived from the CO observations (obs1). The largest differences occur during wintertime and early spring, arising from any combination of errors in transport and mixing, and in the emission inventories of CO and CO$_2$ (Fig. 4.6).

Figure 4.6: Late winter- and springtime pollution events during which neither observation based nor modeled estimates explain the observed CO$_2$ at Beromünster and Lägern-Hochwacht. Modeled and observed regional CO : CO$_2$ ratios above a threshold which denotes an isoline which includes 90% of the cumulative sum of surface sensitivities [see Oney et al., 2015]. Individual regional signals were spatially disaggregated according to Stohl [1996].
To investigate the potential contribution of errors in the emissions of CO and CO\textsubscript{2} to the largest mismatches, we analyzed the possible dependence of the CO : CO\textsubscript{2} ratios on the air mass origin during two pollution events “late winter” (February 19–28, 2013) and “early spring” (March 20 to April 12, 2013). To this end, a regional CO : CO\textsubscript{2} ratio map during these two anomalous periods was calculated by distributing the observed regional CO\textsubscript{2} and CO signals over the concurrent simulated surface sensitivities applying the trajectory statistics method of Stohl [1996], as in:

\[
\chi_{i,j} = \frac{\sum \chi \cdot \tau_{i,j}}{\sum \tau_{i,j}},
\]

(4.5.1)

where \(\chi\) is the measured mole fraction above background and \(\tau_{i,j}\) are the scaled residence times (horizontal indices \(i, j\)) computed with FLEXPART-COSMO and the summation runs over all observations during a given period. For each time period, this was performed by combining the average concentration fields of CO and CO\textsubscript{2} produced by the trajectory statistics method for both sites separately and dividing the resulting CO\textsubscript{1} and CO\textsubscript{2}\textsubscript{i,j} fields by each other. The same was done with the modeled regional anthropogenic signals \(\chi\) (Fig. 4.6, panels E–H).

During these pollution events, cold, northeasterly winds brought highly CO-enriched air from Eastern Europe resulting in anomalously high CO : CO\textsubscript{2} ratios, which differ substantially from the ratios observed during the rest of the winter and the ratios expected from the CO and CO\textsubscript{2} inventories (Fig. 4.6, panels A–D). Applying three-hourly ratios \(R_{\text{mod,3hr}}\) (obs4) to convert observed regional CO\textsubscript{A} to CO\textsubscript{2, A} results in a similar overestimation of CO\textsubscript{2} since the modeled ratios are on average close to those observed during the rest of the winter, further supporting the conclusion that these events were anomalous. Because we use the same observed CO\textsubscript{2} to CO ratio for the entire winter and year (obs1), these special situations cause this ratio to increase, resulting in the underestimation of the anthropogenic component (by obs1) during the rest of the year, and thus a positive bias in the estimated biospheric signal.

During these events, the simulated CO\textsubscript{2} concentrations, and regional CO\textsubscript{2} and CO signals (mod1) are too low relative to the observed ones (Fig. 4.6, panels E–H). This suggests that the inventories do not account for these relatively large emissions. Specifically, it suggests that our employed inventories are strongly under-representing CO and CO\textsubscript{2} emissions in Eastern Europe. A general underrepresentation of CO emissions over Europe during winter was recently also reported by Stein et al. [2014] and Giordano et al. [2015]. A large share of coal and wood for domestic heating is likely responsible for larger emissions, especially CO and thus CO : CO\textsubscript{2} emission ratios in the eastern portions of Europe, specifically during the cold seasons. Current emission inventories do not seem to capture these differences adequately.

4.5.4 Biospheric signal

4.5.4.1 Evaluation

The afternoon (12-15 UTC) time series of our observation-based estimate of the biospheric signal (obs1) shows the expected release of CO\textsubscript{2} during winter and uptake of CO\textsubscript{2} during the spring to fall period (Fig. 4.7), reflecting the seasonal cycle of the balance between photosynthesis and ecosystem respiration, i.e., NEE. The biospheric signal typically varies between 0 to 5 ppm in winter, but varies from \(-5\) to \(-10\) ppm in summer with individual larger excursions in the range of \(-20\) to \(+20\) ppm. This variation indicates the high sensitivity of NEE to the environment. However, a framework for evaluation of the biospheric signal has yet to be established in this context. We evaluate our wintertime observation-based biospheric signals using FLEXPART-COSMO and VPRM simulations, when biospheric signals are typically small with low variability, and rely on the statistical distributions of the derived biospheric signals as a measure of plausibility. During summer afternoon, simulated atmospheric transport is usually most realistic, and therefore this time is
Figure 4.7: Afternoon (1200–1500 UTC) biospheric CO$_2$ signals at Beromünster and Lägern-Hochwacht during 2013. The modeled (mod1) and observation-based (obs1) biospheric signals (CO$_2$,B) are also shown in panel D of Figs. 4.2 & 4.3. The uncertainty (gray) enveloping the residual biospheric signal (obs1) accounts for the uncertainty introduced by the observation based background and anthropogenic CO$_2$ signals.

The VPRM-based modeled signals follow the same seasonal trend as the two residual time series with slightly positive values in winter and pronounced negative values in summer. During the growing season it follows the variations in the residual time series closely, except for a few weeks in summer with negative excursions, especially in July. During these periods, the total model simulated concentrations (Figs. 4.2 & 4.3, panel A) are lower than the observations suggesting that VPRM overestimates the biospheric sink in summer. Apart from this issue, the wintertime VPRM-based time series appears to be a plausible benchmark on which to evaluate the residual biospheric signals. This conclusion is also supported by Ahmadov et al. [2007] and Ahmadov et al. [2009] who demonstrated that VPRM combined with a regional scale transport model is able to capture the main observed features of the observed CO$_2$ distribution well.

During wintertime, when the biospheric signal is expected to be small and positive, owing to photosynthesis being negligible and both plant and soil respiration being weak, the time-series and distribution of VPRM-based biospheric signals fulfill these expectations (Fig. 4.8 & 4.9A,E). The wintertime model-based residual biospheric signal (mob1) shows unrealistically large fluctuations (bias-corrected RMSE [BRMSE] of mob1 versus mod1: BRM 28.2 ppm & LHW 50.4 ppm), which results from the inability to correctly represent CO$_2$,BG and CO$_2$,A concentrations. The observation-based biospheric signals (obs1-obs4) are considerably
closer to the expected biospheric signal with much less scatter (BRMSE of obs1 versus mod1: BRM 4.2 ppm & LHW 8.3 ppm) and are therefore more realistic. However, during the late winter and spring pollution events, when CO-enriched air masses were advected from Eastern Europe, both observation- and model-based methods failed to yield realistic residual biospheric (Sect. 4.5.2). Here, the modeled CO$_2$B (mod1) is likely the most realistic. These examples illustrate well the consequences of inaccurately estimating the “other” CO$_2$ components.

During summertime afternoon (1200–1500 UTC), the model-based residual biospheric signal (mob1) is much more reliable than during wintertime, as is commonly assumed in regional biospheric flux inversion studies [e.g. Goaekede et al., 2010a; Tolk et al., 2011; Meesters et al., 2012], for two reasons. First, uncertainties in model transport are comparatively low since the depth of the ABL, which is a major component of this uncertainty, is largest during summertime afternoons and well-represented in numerical weather forecast models [Brunner et al., 2015]. Second, the anthropogenic signal is small as it is diluted within the well-mixed, deep ABL. There is good agreement (BRM: 4.2 ppm & LHW: 3.9 ppm BRMSE) between the model-based residual (mob1) and the observation-based biospheric signal (obs1) time-series (Fig. 4.7) and statistical distributions (Fig. 4.9C,G) during summertime afternoon. This supports the notion that the observation-based method is suitable to determine summertime biospheric signals. As a side note, during summertime at night (0000–0300 UTC), when predicting atmospheric mixing becomes difficult, differences increase somewhat (BRM: 6.6 ppm & LHW: 6.8 ppm BRMSE). This possibly indicates a further advantage of observation-based signals in that the method offers a possibility to evaluate transport and surface flux inventories during periods atmospheric mixing is most difficult to predict.

Accounting for weekly or three-hourly time-dependence of the anthropogenic CO$_2$ : CO ratio $\beta$ (obs3, obs4)
surprisingly did not significantly improve expected positive definiteness and generally small variability of biospheric signals (Fig. 4.8). Ideally, if the temporal and spatial variability of anthropogenic CO and CO$_2$ emissions were accurately represented in the model, the obs4 method should work best. Such variability, however, appears to be poorly represented in the emission inventories and/or temporal emission profiles. Currently, a fixed annual $\beta$ (obs1 or obs2) appears to be the most robust approach.

The observation-based estimates depend on choices made when determining background and anthropogenic CO$_2$ signals, and the choice of observation site used for the background signal was found to have the largest effect on determining both the CO$_A$ and the accompanying $\beta$ and by extension the resulting residual biospheric signals (Fig. 4.9). The method employing the target site observations for determination of the background and anthropogenic signals (obs5) fails to capture the background CO signal (see Fig. 4.4), and thus fails to capture the regional CO$_2$ signal. It appears to represent a more local CO$_2$ signal. Here, we reiterate the preference for the use of Jungfraujoch observations for determination of the background signal and by extension CO$_A$ and $\beta$ in order to avoid possible biases in the residual biospheric signal, when applying our observation based method.

The estimated uncertainty of observation-based residual biospheric signal (obs1) is dominated by the uncertainty of the anthropogenic CO$_2$ signal, which scales with anthropogenic CO (see Eq. (4.4.2)). It is therefore lowest during summertime and highest during wintertime (Figs. 4.7 & 4.8), when the anthropogenic signal is greatest. However, simplifying assumptions of atmospheric CO chemistry likely result in artificially low uncertainty estimates, which could be corrected upwards based on the expected additional variation in CO,
in a regional inversion framework. Still, a transport model is necessary in order to invert the CO$_2$ signals, and therefore model transport error would still be introduced, albeit at a later stage, with likely weaker effect. In other words, our proposed method does not release regional-scale flux determination from the problem and task of improving atmospheric model transport.

4.5.4.2 Relation to environmental factors

Next, we address whether the variations in the observation-based biospheric residual (obs1) can be plausibly related to environmental drivers. In general, net photosynthesis has been found to be controlled by available photosynthetically active radiation (PAR), soil moisture, CO$_2$, nutrients, and leaf level temperature [Bonan, 2008]. In contrast, heterotrophic respiration is mainly a function of soil temperature and soil moisture. Relationships between these environmental variables and net ecosystem exchange (NEE) were also established by eddy flux covariance measurements, which indicated that the local meteorological variables PAR, temperature, and soil moisture are the most important factors explaining the observed variability [Baldocchi et al., 2001; Baldocchi, 2008; Beer et al., 2010]. Here, we analyze our residual biospheric signal during the growing season (May to August) with meteorological variables as extracted from the COSMO-2 model analysis and interpolated to the location of the two measurement sites. The analyzed variables are temperature (averaged of preceding 24 hours), PAR (accumulated over the preceding 24 hours), as well as precipitation (accumulated over the preceding 21 days) as a proxy of soil moisture.

During the growing season the biospheric residual was mostly negative indicating biospheric uptake of CO$_2$ (Fig. 4.10) but also large variations on synoptic time scales were observed including periods when the biospheric residuals became positive, indicating a net biospheric source of CO$_2$. Two periods in mid-June and late July/early August with positive biospheric residuals clearly corresponded to especially warm conditions with daily average temperatures between 20$^\circ$C and 25$^\circ$C and daytime maximum temperatures around 30$^\circ$C (Fig. 4.10). At these high temperatures, photosynthetic activity may largely cease since stomata tend to close to avoid excessive transpiration. This may be further assisted by diminished leaf-level water availability. Furthermore, these periods occurred towards the end of the agricultural growing season when a large fraction of crops (esp. cereals) were already harvested and additional hay harvesting may have further reduced photosynthetic uptake by grasslands. This idea is supported by previous conclusions that the summertime surface sensitivity of both sites is dominated by crop- and grasslands and only to a lesser degrees by forests [Oney et al., 2015]. We also observe a lag (∼1 day) between increasing temperature and the biospheric response i.e. positive biospheric signals, which supports the notion that these environmental factors drive biospheric signal variation.

A closer, somewhat qualitative examination of the relationship between the biospheric residuals (obs1) and the environmental variables was carried out by fitting a non-parametric generalized additive regression model [GAM Wood and Augustin, 2002] to the biospheric residuals using the meteorological variables as predictors. This analysis was limited to specific meteorological situations (convective weather and afternoon values 1200–1500 UTC) in order to limit the influence of atmospheric transport and mixing on the observed biospheric residuals. The data from both sites were jointly analyzed in a single GAM, since similar response functions were expected at both sites due to their proximity. We observed the expected relationship between biospheric residuals and PAR with increasingly negative biospheric CO$_2$ signals with increasing PAR (Fig. 4.11). For 21-day-accumulated precipitation as a proxy for soil moisture the relationship was less clear but a tendency towards reduced biospheric activity under dry conditions appeared. With temperature, a form of threshold behavior was observed, where at 24-hour mean temperatures > 20°C the apparent terrestrial Swiss Plateau carbon sink turned into a net CO$_2$ source. This temperature is within the range of other studies that showed a drop-off of photosynthesis above a critical temperature of 30°C [e.g. Leuning, 2002], which may also be a bit low for a signal predominantly from grasslands. However, the combination of the acclimation
Figure 4.10: Observed afternoon (1200–1500 UTC) biospheric CO$_2$ signals (obs1) along with temperature (average of past 24 hours), photosynthetically active radiation (PAR) accumulated over the past 24 hours, as well as precipitation accumulated over the previous 21 days (as a proxy of soil moisture), during the main growing season (01 May–01 September) of 2013 interpolated from COSMO-2 analysis fields to the observation site positions, Beromünster and Läger-Hochwacht at 250 m above model ground level. Shaded areas demarcate periods during which the average temperature of the preceding 24 hours was > 20° C.
4.6 Conclusions

We present a simple and effective method to derive the biospheric signal in atmospheric CO$_2$ mole fractions using co-located CO$_2$ and CO observations. Relative to many previous studies, where the biospheric signal was estimated by using model-based estimates of the background and the anthropogenic signals, this method circumvents the introduction of model transport error and inaccuracies of surface flux inventories into the residual biospheric CO$_2$ signals. The error in these two components might be as large as ±20% [Peylin et al., 2011], which our method could substantially reduce. Nonetheless, a transport model would still be necessary in order to estimate the biospheric CO$_2$ surface fluxes from the observation-based biospheric signal. Therefore, considerable effort is still necessary to improve the skill of atmospheric transport models.

The observation-based methods (obs1 and obs2) using single annual CO : CO$_2$ apparent emission ratios performed well at our two CarboCount CH sites, but these ratios are site-specific and likely useful mainly for observation sites removed from large anthropogenic CO$_2$ and CO sources. Prominent examples of when these methods fail are when anomalous, large-scale pollution events with distinctly different emission ratios occurred. Emissions from large-scale biomass burning would cause an analogous situation. Furthermore, these large variations in the CO$_2$,A : CO$_A$ ratios would prevent the use of constant ratios. We expect that the methods using the time-dependent modeled CO$_2$,A : CO$_A$ ratios would perform better in environments where large variations in CO$_2$,A : CO$_A$ occur.

We emphasize the need to have consistency between CO and CO$_2$ inventories when developing the CO$_2$,A : CO$_A$ apparent ratio from model simulations [Vogel et al., 2010; Peylin et al., 2011]. Given a rigorously defined background CO and CO$_2$ signal, the proposed scaling of CO$_A$ into CO$_2$,A would provide a method compatible with regional carbon budget studies. This would offer the opportunity to evaluate both anthropogenic and biospheric flux inventories. Given both increasing and increasingly uncertain anthropogenic emissions

Figure 4.11: Response of observed afternoon (1200–1500 UTC) biospheric CO$_2$ signals (obs1) to modeled (described in Fig. 4.10) PAR, accumulated precipitation, and average temperature at both Beromünster and Lägern-Hochwacht during the growing season (01 May–01 September) of 2013. We narrowed our investigation to convective meteorological situations according to the categorization by Weusthoff [2011]. The blue line corresponds to a generalized additive model binned by the 95% confidence interval.

of plants [Kattge and Knorr, 2007; Groenendijk et al., 2011] to the cold spring, ensuing shock of a short but intense heatwave of June and ensuing sunny summer [MeteoSwiss, 2014] may help to explain these large and positive biospheric signals during a year with average temperatures [relative to 1981–2010 MeteoSwiss, 2014]. Furthermore, these observations may have also been influenced by co-occurrence of these high temperatures with agricultural harvests, particularly of hay.
[Ballantyne et al., 2015], this method might also provide an approach to monitor anthropogenic emissions, complementing the $^{14}\text{CO}_2$-based method [Gamnitzer et al., 2006; Vardag et al., 2015].

This study highlights the advantages of co-located CO$_2$ and CO observations. The observation of additional gas species useful in determining the background and anthropogenic signals will definitely improve the ability to estimate and understand the biospheric signal, and in the end hopefully reduce the uncertainty of the inversely estimated sources and sinks of atmospheric CO$_2$ over terrestrial systems. Because anthropogenic CO$_2$ emissions constitute the largest net CO$_2$ flux of Europe [Ciais et al., 2010b], an emission verification system would bolster mitigation efforts. We therefore stress the need for co-located CO$_2$ and CO observations in such a verification system.

Acknowledgements

This study was funded by the Swiss National Funds (SNF) as part of the “CarboCount CH” Sinergia Project (Grant Number: CRSII2_136273). We acknowledge the use of the trace gas observations carried out by Martin Steinbacher, Empa, at the High Altitude Research Station Jungfraujoch run by the International Foundation (HFSJG), in the framework of the Integrated Carbon Observation System in Switzerland (ICOS-CH), SNF Grant 20FI21_1489921. We also acknowledge MeteoSwiss for the provision of their operational COSMO analysis products. We thank Christoph Gerbig for discussions, provision of the VPRM NEE flux data, and his very helpful comments on an earlier draft of this paper. We thank Frederic Chevallier for providing global CO$_2$ reanalysis fields (MACC-II, v13r1). The FLEXPART-COSMO simulations were conducted at the Swiss National Supercomputing Center CSCS. We also acknowledge MeteoSwiss for the provision of their operational COSMO analysis products.
Chapter 5

Synthesis and outlook

My work encompassed two major components of top-down surface carbon flux determination: atmospheric CO$_2$ mole fraction measurements and their simulation. My goal was to thereby contribute by using these observations with an atmospheric transport model to estimate the biospheric carbon flux of the Swiss Plateau. Toward this broader goal as a part of the CarboCount CH project, I have successfully:

- constructed and maintained the atmospheric carbon monitoring site Lägern-Hochwacht,
- described likely drivers of the variability observed at this and the other CarboCount network measurement sites,
- simulated observed CO$_2$ mole fractions using the high-resolution atmospheric model FLEXPART-COSMO of the site-wards transport of anthropogenic and biospheric carbon fluxes,
- investigated the relationship between CO and CO$_2$ observed at the Beromünster and Lägern-Hochwacht sites,
- employed this relationship to develop a technique to isolate the biospheric CO$_2$ signal based solely on observed mole fractions.

These larger tasks consisted of many smaller tasks and, in the process of completing these tasks, much was learned. Practical recommendations for future collaboration can be offered from this experience. Beyond that, future research tasks and directions informed by this work are also offered.

5.1 Summary

The measurement system at Lägern-Hochwacht was described in Chapter 2 and has performed reliably for more than three years now, except for a pump failure. The remaining CarboCount CH sites Beromünster, Gimmiz, and Früebüel have also performed very well, but had similar issues with the PICARRO suction pump. Overall, the CarboCount CH network provides precise and accurate atmospheric carbon observations that are within WMO-established quality guidelines [Tans and Zellweger, 2014] with excellent temporal coverage (> 95%). The reported uncertainties of these observations are taken from the target gas calibrations, because directly estimated uncertainties of the observations appear to be biased low. This is likely due to the insufficient accounting for the uncertainties introduced by the determination of cylinder mole fractions, the drifts in instrument baseline and sensitivity in between span calibrations, and/or the insufficient equilibration of gas concentrations after valve switching, or other unidentified sources of uncertainty. Further investigation
will be needed to better understand this discrepancy. But this also serves to emphasize the importance of target gas measurements.

In Chapter 3, the evaluation of the meteorology simulations highlighted various challenges for the atmospheric transport model at the different observation sites including the representation of topography-induced flows and the nocturnal boundary layer. Due to the site locations and the generally complex Swiss topography, the trend towards higher resolution is warranted here and would likely aid in reducing uncertainties related to atmospheric transport. This is especially true for the Lägern-Hochwacht observation site surrounded by steep topography, and for the site Früebüel located on a mountain plateau. Simulated nocturnal mixing appears to be overestimated in the analysis fields of the COSMO-2 model, which drive FLEXPART-COSMO. However, especially at Beromünster, the model simulations of wind and temperature are in excellent agreement with the observations on average as demonstrated by the comparison of wind roses and mean diurnal cycles. Furthermore, FLEXPART-COSMO surface sensitivity simulations at each site correspond to interpretations of the site’s observations. Overall, it was found that COSMO and FLEXPART-COSMO are suitable tools to investigate carbon fluxes over the Swiss Plateau.

The observation site characteristics relevant to regional-scale modeling suggests that Beromünster and Lägern-Hochwacht provide observations useful for long-term carbon flux studies over the Swiss Plateau. These sites appear to be less sensitive to diurnal fluctuations due to their sampling above the nocturnal boundary layer. Furthermore, these sites have sufficient sensitivity to the entire Swiss Plateau. Sampling at high elevation appears to be an additional advantage in winter when the atmosphere is more stratified and, therefore, near-surface sites appear to be sensitive mostly to their immediate surroundings. Therefore, the near-surface sites Früebüel and Gimmiz provide observations that will need temporal filtering or may be used as evaluation sites, in that their observations are compared with simulations with inverted carbon fluxes, similar to Henne et al. [2016]. Despite its location in one of the most flat areas of Switzerland, Gimmiz turned out to be especially challenging due to a very stable nocturnal boundary layer that the model was unable to reproduce.

In Chapter 4, we developed and evaluated a CO-based method to determine the regional biospheric signal in atmospheric carbon dioxide using the observations of Beromünster and Lägern-Hochwacht. We found that the CO$_2$ mole fractions observed during the year of 2013 at the CarboCount network sites contained considerable anthropogenic signals, which, if not completely removed, would be mapped to the biospheric signals and thus biospheric fluxes. The regional biospheric signal is typically a small component of the observed CO$_2$ mole fraction relative to the combined large-scale background and regional anthropogenic emission signals. Isolating this signal is very challenging, and any errors in the quantification of the background and anthropogenic CO$_2$ components will translate into errors in the biospheric residual of CO$_2$ observations. Such errors could arise due to imperfectly known anthropogenic emissions, biases of background mole fractions, and/or inaccurately simulated atmospheric transport. However, we found that observations from Jungfraujoch provide information on background CO$_2$ and CO signals. Furthermore, the site’s CO observations above these background signals provide information on regional anthropogenic CO$_2$ signals. These sources of information can thus provide an opportunity to circumvent the pitfalls associated with modeling the background and regional anthropogenic CO$_2$ signals, and allowing an observation-based derivation of the regional biospheric CO$_2$ signal.

Different approaches were taken to determine the biospheric CO$_2$ signals on the basis of CO$_2$ and CO observations. Determination of background signals was carried out with the “robust estimation of the baseline signal” (REBS) using data from the two sites as well as from Jungfraujoch. We found the choice of background site to be very important as it determines the spatial representativeness of the regional signals above the background and, thus, also the observed apparent anthropogenic CO/CO$_2$ ratio. The use of Jungfraujoch appears to be the best choice since the Jungfraujoch-derived background signals are similar to the modeled background. Furthermore, using the site’s observations with the REBS method still yields good performance.
but produces biospheric signals that appear to be of a scale smaller than the desired regional scale, and are thus less useful in this context. Except for a few events when cold, easterly winds brought anomalously CO-enriched air, the method outperforms the standard, model-based method deriving plausible, continuous biospheric signals.

Qualitative interpretation of the resulting biospheric signals indicate a biospheric carbon sink over the Swiss Plateau during the major growing season of 2013 (May to August). Furthermore, biospheric signals show a positive relationship with air temperature, where temperatures above a daily mean of $\sim 20^\circ C$ may correlate with a weakened Swiss Plateau carbon sink. Although the weather during 2013 was average relative to the climate of 1981–2010, the early winter and spring months were cold, and were followed by a hot summer. It is possible that Swiss Plateau vegetation had acclimated to cold spring temperatures, which were followed by hot summer weather to which the vegetation was not acclimated. This warm weather may have played an important role, but also likely coincided with agricultural harvests.

### 5.2 Lessons learned

The multifaceted work of environmental science in general and carbon cycle science in particular entails the management of many technical details and pitfalls. These seemingly (or scientifically) unimportant aspects may finally require the most attention or, in some cases, skew results. Exchange with more experienced researchers has inevitably saved both time and frustration. A selection of these lessons learned are offered here.

Data acquisition from the field needs to be continuous, automated, and occur within a short period (< 1 day) of collection in the field. Automated data quality checks helped to assure good temporal coverage. Yet, dedicated personnel contributed most to good temporal coverage of data by maintenance, and facilitating the exchange of experience and knowledge.

Reliability of field-deployable measurement devices is paramount to reducing costs of long-term carbon cycle observation. We second the experiences of Richardson et al. [2012] with PICARRO devices, but with one caveat. From our experience, PICARRO pumps are not very reliable and should be used solely as an ersatz, regardless of improvements claimed by PICARRO. The current KNF pump (see Table 2.3) has as of now operated for 3 years without issue. At the very least, a readily available replacement pump is necessary in case of failure, similar to the broader modular system described in Andrews et al. [2014].

As Leuenberger et al. [2015] have demonstrated, steel cylinders are not suitable for long-term storage of greenhouse gases, as mole fractions need to be known with high accuracy and exhibit high stability over time. Based on the recommendations from the in-house GAW World Calibration Center (Zellweger and Steinbacher, pers. comm.), we have employed aluminum cylinders, and can further give this recommendation. However, we have yet to remeasure all reference gas cylinders within the project. Specifically, slow mole fraction drifts, especially in CO, have also been observed in aluminum cylinders in the past (Zellweger and Steinbacher, pers. comm.).

The measurement system at Beromünster is by far the most sophisticated of those developed within the project. It can sample multiple heights within an hour's time, has an additional separate set of sampling lines, and can sample a large number of standard reference gases [Berhanu et al., 2016]. The comparatively simple setup at Lägern-Hochwacht nevertheless resulted in reliable and accurate measurements with much lower maintenance requirements and lower initial costs. The setup included a simple box for switching between reference gases and ambient air, with no external computer but direct control of valves and operation modes through the PICARRO instrument, only three reference gas bottles with high and low standards and a target, and a simple USB stick for broadband data transmission. Such a setup could be a valuable model for the
operation of low-cost sites, complementing the more challenging and expensive setup required, e.g., for sites of the ICOS network.

Atmospheric transport models driven offline, i.e. with external meteorology, can offer improvements in accuracy and computational efficiency of transport simulations. Offline transport simulations require accurate driving meteorology which needs evaluation. Analysis meteorological fields, having been corrected to better agree with observations, may contain artifacts introduced by the assimilation procedure. Although unpublished, the COSMO-2 wind fields, which were evaluated in Chapter 3, are analysis fields which record an instantaneous snapshot of wind every hour. Visual inspection of these high-resolution wind fields near the ground reveals anomalously strong variations in the vertical wind component. When used to drive FLEXPART-COSMO simulations, this resulted in too strong mixing and, as a consequence, in the regional transport simulations, which greatly underestimated regional signal strength. Two solutions to minimize this problem were to use coarser resolution (0.06° versus 0.02°) meteorological fields, as was done in Chapter 4, and, for future studies, to use time-averaged instead of instantaneous meteorological fields. Here, caution is warranted and evaluation of offline meteorological fields is necessary.

Much of the work of this project was done devising and implementing computer-based programs to prepare data, run simulations, and analyze and visualize results. Shared computing facilities for project members helped to facilitate collaboration and to increase efficiency of computer resource use. Large data sets, such as driving meteorology, had only one centralized copy. Furthermore, resource use could be monitored which can lead to better support of scientific work. Debugging of large computer programs was also facilitated by the common computer architecture. Common computing facilities carries numerous advantages.

The carbon cycle is least understood on time-scales greater than one year, but this does not correspond to the typical time-scale of research. Throughout these experiences, two recurring themes appear and center around the necessity of long-term carbon cycle observation and research. The two pillars of measurement and modeling require both long-term infrastructure and dedicated personnel. These are critical for success in unraveling and understanding the carbon cycle on the regional scale. However, short-term research projects, such as CarboCount CH, GAUGE [Pitt et al., 2016], CarboEurope [Dobman et al., 2006], Mid-Continental Intensive campaign [Miles et al., 2012], have helped to guide long-term infrastructure and research such as ICOS and the US tall tower network. Furthermore, tall tower “super sites”, where many chemical and meteorological variables are observed, are appearing as a critical element of long-term observation, but are too expensive and impractical for these guiding short-term projects. However, a site’s placement and equipment needs careful deliberation, for which such short-term projects are well-suited.

5.3 Outlook

The complexity of the land surface flux dictates many different approaches, all of which can be improved. Prioritizing which approach should be addressed next is difficult and is best informed by experience. The following outlook offers future research tasks and directions which, in my view, will lastingly advance the state of carbon cycle science of the Swiss Plateau.

The interplay between observational and modeling studies drives carbon cycle research. CarboCount CH represents one of the first interdisciplinary projects to tackle the Swiss carbon balance and has laid the foundation for future observational and modeling studies. Continued, long-term Swiss monitoring efforts such as the ICOS-CH (http://www.gl.ethz.ch/research/bage/icos-ch.html) are facilitated by the modeling expertise of the Center for Climate Systems Modeling (C2SM) at the ETH Zurich, for example. Furthermore, the experience and infrastructure observing the carbon cycle has been augmented by the CarboCount CH project through its network. Hopefully, future studies will continue to be highly interdisciplinary.
The regional-scale simulation of CO$_2$ mole fractions requires great effort to represent lateral boundary conditions and surface fluxes, as well as atmospheric transport modeling. This thesis details the tremendous work put into this task. The performance of the “standard method” in simulating observed CO$_2$ concentrations is encouraging, and demonstrates the ability of FLEXPART-COSMO to simulate atmospheric transport, the accuracy of the Swiss emissions inventories, and the potential of the relatively simple VPRM model. Although improving the accuracy of these surface fluxes is beneficial, improving the accuracy of atmospheric mixing of COSMO and FLEXPART-COSMO would likely yield the greatest benefit to future biospheric flux inversion studies.

Land-to-atmosphere flux datasets contain a great deal of spatial and temporal information. However, these data are necessarily aggregated to reduce for the high complexity of landscapes and the associated carbon fluxes. Prioritizing inclusion of further the biospheric and anthropogenic surface flux processes for Switzerland would likely include agricultural carbon fluxes. Crop models of varying complexity “grow” crop vegetation given environmental input such as sunlight, temperature, precipitation, and/or fertilizer. The Community Land Model (CLM) has such a crop scheme [Levis et al., 2012], which is being actively developed and increasingly used [Drewniak et al., 2013; Bilionis et al., 2015; Lu et al., 2015]. Within the CarboCount CH project much effort has gone into efficiently coupling CLM to COSMO and, in a next step, this system should be further developed to simulate agricultural carbon fluxes over the Swiss Plateau. As indicated in Chapter 3, local fluxes, possibly those of nearby vegetable crops, likely explain the highly enriched CO$_2$ observations at Gimmiz. Furthermore, approximately 4 Tg a$^{-1}$ of Swiss agricultural primary production are reported [Meyre, 2016], not including what is left on the field. Given a composition of approximately 5% elemental carbon (from $\sim$90% water content and $\sim$50% C of dry mass), this amounts to approximately 200 Gg C harvested and transported away from fields. This is a significant number which warrants further investigation and refinement, and would likely improve accuracy of surface flux data sets, and by extension CO$_2$ mole fraction simulations.

The proposed method of scaling CO above a background CO signal into anthropogenic CO$_2$ depends on having an accurate apparent anthropogenic CO/CO$_2$ ratio, but this ratio is known to vary with time. Using time-dependent modeled ratios to account for this variability did not significantly improve the performance of this method, but it appears that this is due to uncertainties in the emissions inventories or atmospheric transport. Improving the accuracy of anthropogenic emissions inventories of CO and CO$_2$, both in spatial distribution and temporal signature, along with improved atmospheric transport simulations, would likely help to better understand the anthropogenic CO$_2$ signal.

Carbonyl sulfide observations, a tracer of stomatal exchange, would offer an independent alternative method to evaluate these observation-based biospheric signals. The Beromünster observation site with its multiple sampling heights would provide ideal observations to test whether the observation-based biospheric signals still contain anthropogenic CO$_2$ signals. Given this infrastructure, this could be carried out long-term and would likely help to improve the accuracy of this method.

Looking ahead, the application of this method to the observations from 2013 to 2015 helps to illustrate the variable response of vegetation to weather (Figure 5.1). The weather (cold spring and hot summer) of 2013 was anomalously variable although it averaged to be normal. The following growing season was opposite; it was preceded by a very warm winter and the high temperatures continued through the spring but were followed by a relatively cold and extremely cloudy and wet summer during 2014 [MeteoSwiss, 2015], during which less negative biospheric signals, i.e. weaker photosynthesis, were observed. Small-scale, eddy covariance observations have however observed the opposite; that is, diffuse radiation correlated with higher photosynthesis and thus NEE [for forest ecosystems Law et al., 2002]. Further work is necessary to illuminate this contradiction.

During the very warm growing season of 2015 [MeteoSwiss, 2016], the vegetation across the Swiss Plateau
does not appear to have grown very well in the warm and sunny weather during spring and summer or ecosystem respiration appears to have increased enough to offset CO$_2$ uptake. Assuming that these interannual differences between the biospheric signals represent the effect of differing weather conditions on vegetation, the connection between higher temperatures and more positive biospheric signals, related to a weaker carbon sink, is apparent but is not very robust and varies between years and sites (Figure 5.2). Specifically, comparing the observed regional biospheric signals of 2014 and 2015 with 2013, we see highly positive CO$_2$ signals of both colder and wetter, and hotter and drier growing seasons of 2014 and 2015, respectively, relative to 2013 (Figure 5.1). Yet, when we correlate observed temperature with biospheric signals (Figure 5.2) in an approach similar to that detailed in Chapter 4, no robust pattern appears. Why do we observe these varying responses of biospheric CO$_2$ to changing temperatures? This likely means that simply correlating the biospheric CO$_2$ signal with local temperature is a poorly suited approach to understand observed biospheric signal variability, but also hints at the complexity of the relationship between weather and carbon fluxes.
Further analysis will likely shed light on these highly variable observations. Finally, it is questionable whether these biospheric signals contain biases. Accompanying model studies may reveal this possible caveat, and, although the observation-based approach to deriving biospheric CO$_2$ signals presented here was found to be valid in Chapter 4, further model work and/or carbonyl sulfide observations would help to evaluate these biospheric signal estimates.

Gimmiz observes large variability mainly due to ABL dynamics and potentially large surface carbon fluxes. Although certainly difficult to reproduce, these observations could provide a benchmark for regional-scale carbon flux modeling of the Swiss Plateau. Eugster and Siegrist [2000] first documented nighttime accumulation and identified mesoscale airflow as the main driver of this variability. Given observed wind speeds, it is unlikely that mesoscale transport of atmospheric carbon can explain the strong accumulation at night which consistently results in an increase of several hundred ppm CO$_2$. It is more likely that a shallow and stable nocturnal ABL combined with local, potentially large carbon fluxes causes this. Preliminary studies within this project have indicated that current surface flux inventories and atmospheric transport models largely underestimate nighttime observations. Surface sensitivity simulations indicate that surface fluxes in the Seeland are mostly responsible for this variability. This translates into a considerable amount of atmospheric carbon that accumulates in the nocturnal ABL in the Seeland, which we currently cannot explain. This discrepancy may be due to the atmospheric transport model overestimating nighttime vertical mixing. Significant progress appears to be forthcoming in the form of an improved turbulence scheme in COSMO, which greatly improves nighttime vertical mixing [Raschendorfer, 2016]. Furthermore, the nocturnal radiosondes at Payerne provide...

Figure 5.2: Response of observed afternoon (1200–1500 UTC) biospheric CO$_2$ signals (obs1) and observed temperature averaged of the preceding 24 hours at both Beromünster and Lägerm-Hochwacht during the growing seasons (01 May–01 September) of 2013–2015. Observations shown are only during convective meteorological situations according to the categorization by Weusthoff [2011].
considerable information that would aid in evaluating mesoscale airflow in the employed transport model and thereby the interpretation of the highly variable observations at Gimmiz. Therefore, it would be fruitful to carry out an intense observation campaign in order to best guide the placement of a long-term monitoring site in or near the Seeland. Furthermore, a tower sampling multiple heights would help to uncover and hopefully understand any problems in simulating observed vertical structure of CO\textsubscript{2} mole fractions.

Beyond carbon budgeting, the goal of understanding the relationship between the regional carbon cycle and climate presents a very difficult problem. A biospheric model must be calibrated to reproduce flux and/or mole fraction observations together with an atmospheric transport model. Here, the VPRM showed promising ability to simulate the biospheric signal and should be simple enough to calibrate in a transparent manner, which would aid understanding the carbon cycle-climate relationship. However, in its current implementation in CarboCount CH, it is driven by coarser ECMWF meteorological output, which has different topography and, most importantly, different land cover. This product is then reprojected to a higher resolution COSMO domain and its influence is simulated. Thereby, an uncertainty of scale mismatch is unnecessarily introduced, where the meteorology that drives the surface fluxes differs from the meteorology that drives transport.

In a peer review of Kountouris et al. [2015], Michalak [2015] warns of the consequences of introducing such uncertainties into inverted fluxes. Such an error can also easily be made with Lagrangian transport models, where the surface sensitivity output and flux inversion grid can be flexibly defined, thereby creating a mismatch of scales. Given the simplicity of VPRM, implementation within COSMO and even FLEXPART-COSMO, such as in STILT-VPRM [Matross et al., 2006; Pillai et al., 2012], should not be too difficult. This attention to the spatial consistency between driving meteorological input and the flux inversion grid would help to avoid this problem.

To sample the Swiss Plateau, the Beromünster site would likely suffice and would thus greatly contribute to the Swiss ICOS network (http://www.gl.ethz.ch/research/bage/icos-ch.html). Jungfraujoch has been integrated in ICOS-CH, but its observations contain information from far beyond Switzerland and even beyond Europe [Henne et al., 2010]. Beromünster, on the other hand, has been shown to cover the Swiss Plateau throughout the year, and, containing landscapes similar to most of central Europe, arguably provides a greater amount of information about European surface fluxes. Furthermore, global inversion efforts, such as CarbonTracker, would likely be able to integrate atmospheric carbon observations from Beromünster. Finally, from what we found, future atmospheric carbon monitoring efforts should benefit from measuring CO and CO\textsubscript{2}. We have shown this method to be an advantageous approach to avoid introduction of uncertainties from model transport and anthropogenic emission inventories. The interpretation of the biospheric CO\textsubscript{2} signals since 2013 (Figure 5.1) provides insight into the complex relationship between biospheric activity and weather, and the challenges along the path of understanding terrestrial carbon fluxes on longer time-scales.
Appendix A

Measurement data processing code

A.1 Introduction

This document describes the technical aspects of the processing and calibration of the trace gas measurement data collected as part of the SNF Sinergia Project CarboCount CH (http://carbocount.ch/).

A.1.1 Site- and time-specific valve information

The following tables hold the information about the valve positions of the measurement system at each site. Specifically, what was measured from the date of the table, until the next table. For example, the first table with the date "2012-08-23-140000" in the section title is valid for the site Laegern from 2012-08-23 at 2 p.m. until the next table (when I replaced a bottle) dated 2012-09-28 replaces the valve information. See Table A.2 for another example. The R-function check.site.info efficiently checks whether the site information held within the R-object site.info is valid for the particular date and time. The naming of the files must be (in POSIX notation) SiteInfo-%Y-%m-%d-%H%M%S.csv.

A.1.1.1 Example: SiteInfo-2014-08-21-090000

A.1.2 Site- and time-specific measurement device and calibration information

The following tables hold the information about the measurement devices at the respective measurement sites. Similar to the SiteInfo-* files/tables (see Table A.1), a table is valid after the date-time held in the file name, until the next table. For example, the first table with the dated name "SiteDeviceInfo-2012-08-23-1400000" in the section title is valid for the site Laegern from 2012-08-23 at 2 p.m. until the next table (when the first successful span calibrations at Lägern-Hochwacht were carried out) dated 2012-11-19 replaces the calibration and measurement information. Another example, is the different measurement device placed at Beromünster after failure of the measurement system and before the reinstallation of the primary device. This information is handled and recognized with the R-function check.device.info, which efficiently checks whether the site information held within the R-object site.device.info is current. Table A.1 is an example of such information. Similarly, the naming of the files must be (in POSIX notation) SiteDeviceInfo-%Y-%m-%d-%H%M%S.csv, and these are in CSV-format, without quotes. These files can be found in: /remote2/CarboCountCH/CarboCountDB/Documentation/ and are also under version control.
Table A.1: The latest table (site.info) from 2014-08-21 at 09:00:00 UTC, Ruediger Schanda changed the CO high bottle at Gimmiz. This table is written out by this org-mode (emacs) document with R as SiteInfo-2014-08-21-090000.csv in the directory where this file resides. NA stands for ‘not available’.

<table>
<thead>
<tr>
<th>site</th>
<th>type</th>
<th>height</th>
<th>valvepos</th>
<th>nsecskip</th>
<th>duration</th>
<th>bottle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laegern</td>
<td>work</td>
<td>NA</td>
<td>24</td>
<td>540</td>
<td>900</td>
<td>CB09862</td>
</tr>
<tr>
<td>Laegern</td>
<td>high</td>
<td>NA</td>
<td>17</td>
<td>540</td>
<td>900</td>
<td>CB09870</td>
</tr>
<tr>
<td>Laegern</td>
<td>low</td>
<td>NA</td>
<td>18</td>
<td>540</td>
<td>900</td>
<td>CB09881</td>
</tr>
<tr>
<td>Laegern</td>
<td>meas1</td>
<td>32</td>
<td>0</td>
<td>540</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Fruebuel</td>
<td>work</td>
<td>NA</td>
<td>9</td>
<td>540</td>
<td>900</td>
<td>CB09886</td>
</tr>
<tr>
<td>Fruebuel</td>
<td>low</td>
<td>NA</td>
<td>10</td>
<td>540</td>
<td>900</td>
<td>CB09789</td>
</tr>
<tr>
<td>Fruebuel</td>
<td>high</td>
<td>NA</td>
<td>12</td>
<td>540</td>
<td>900</td>
<td>CB09884</td>
</tr>
<tr>
<td>Fruebuel</td>
<td>meas1</td>
<td>4</td>
<td>0</td>
<td>540</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Beromuenster</td>
<td>work</td>
<td>NA</td>
<td>1</td>
<td>120</td>
<td>180</td>
<td>LK542087</td>
</tr>
<tr>
<td>Beromuenster</td>
<td>high</td>
<td>NA</td>
<td>2</td>
<td>240</td>
<td>360</td>
<td>CB09863</td>
</tr>
<tr>
<td>Beromuenster</td>
<td>low</td>
<td>NA</td>
<td>3</td>
<td>240</td>
<td>360</td>
<td>CB10095</td>
</tr>
<tr>
<td>Beromuenster</td>
<td>targ</td>
<td>NA</td>
<td>4</td>
<td>120</td>
<td>180</td>
<td>CB09890</td>
</tr>
<tr>
<td>Beromuenster</td>
<td>meas1</td>
<td>212</td>
<td>5</td>
<td>120</td>
<td>180</td>
<td>NA</td>
</tr>
<tr>
<td>Beromuenster</td>
<td>meas2</td>
<td>132</td>
<td>6</td>
<td>120</td>
<td>180</td>
<td>NA</td>
</tr>
<tr>
<td>Beromuenster</td>
<td>meas3</td>
<td>72</td>
<td>7</td>
<td>120</td>
<td>180</td>
<td>NA</td>
</tr>
<tr>
<td>Beromuenster</td>
<td>meas4</td>
<td>45</td>
<td>8</td>
<td>120</td>
<td>180</td>
<td>NA</td>
</tr>
<tr>
<td>Beromuenster</td>
<td>meas5</td>
<td>12</td>
<td>9</td>
<td>120</td>
<td>180</td>
<td>NA</td>
</tr>
<tr>
<td>Beromuenster</td>
<td>meas6</td>
<td>0</td>
<td>11</td>
<td>120</td>
<td>180</td>
<td>NA</td>
</tr>
<tr>
<td>Beromuenster</td>
<td>extra1</td>
<td>NA</td>
<td>12</td>
<td>120</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Beromuenster</td>
<td>extra2</td>
<td>NA</td>
<td>13</td>
<td>120</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Gimmiz</td>
<td>work</td>
<td>NA</td>
<td>1</td>
<td>420</td>
<td>540</td>
<td>CB09873</td>
</tr>
<tr>
<td>Gimmiz</td>
<td>high</td>
<td>NA</td>
<td>2</td>
<td>420</td>
<td>540</td>
<td>CB09861</td>
</tr>
<tr>
<td>Gimmiz</td>
<td>low</td>
<td>NA</td>
<td>3</td>
<td>420</td>
<td>540</td>
<td>CB09885</td>
</tr>
<tr>
<td>Gimmiz</td>
<td>targ</td>
<td>NA</td>
<td>4</td>
<td>420</td>
<td>540</td>
<td>CB09787</td>
</tr>
<tr>
<td>Gimmiz</td>
<td>meas1</td>
<td>32</td>
<td>5</td>
<td>720</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Gimmiz</td>
<td>COhigh</td>
<td>NA</td>
<td>6</td>
<td>300</td>
<td>600</td>
<td>CB09872</td>
</tr>
<tr>
<td>Gimmiz</td>
<td>COlow</td>
<td>NA</td>
<td>7</td>
<td>300</td>
<td>600</td>
<td>556359</td>
</tr>
<tr>
<td>Gimmiz</td>
<td>COmeas</td>
<td>32</td>
<td>8</td>
<td>360</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

A.1.2.1 Example: SiteDeviceInfo-2014-04-29-093800

A.2 Data Processing and Management

Data come from PICARRO, HORIBA and meteorological sensors as raw data in both uncompressed (*dat and *TXT) and compressed (*ZIP or *TXT.gz) form. Furthermore, the R-code needs to be able to account for the repetition of the data within multiple-channel PICARRO (G2401, G2311-f and G2301) data files. The PICARRO devices vary within and across models but range between 20 (G2301) and 30 (G2311-f) measurements per minute (0.3–0.5Hz) per species. That is, to calculate the means and uncertainties correctly, one needs to use the data which are only from the measurement of a particular gas, which are repeated in PICARRO output, as indicated by the species column.

A.2.1 Data processing code

The data processing code is a set of bash-scripts and R-functions the latter of which are organized and documented in the custom R-package cccDataProc (see below). General functions handle every site, for a common interface. The initial reading of data is the only exception to this where site-specific code is used.
### A.2. Data Processing and Management

Table A.2: The latest measurement device and calibration information from 2014-04-29 at 09:38:00, when the normal device at Beromünster was put back into service, replacing the ersatz G2311-f. This table is queried when calibration parameters are calculated (defining the calibration type) and raw data are checked to see whether they are feasible (e.g., is CO₂\textsubscript{dry} > 6%?). For example, this table is written out by this org-mode document with R as SiteDeviceInfo-2014-04-29-093800.csv in the directory where this file resides. NA stands for 'not available'.

<table>
<thead>
<tr>
<th>site</th>
<th>id</th>
<th>gas_name</th>
<th>limit</th>
<th>cal_type</th>
<th>Device</th>
<th>meas_per_min</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laegern 1</td>
<td>1</td>
<td>CO₂\textsubscript{dry}</td>
<td>6</td>
<td>p₂ f</td>
<td>CFKADS2043</td>
<td>24</td>
</tr>
<tr>
<td>Laegern 2</td>
<td>2</td>
<td>CH₄\textsubscript{dry}</td>
<td>0.006</td>
<td>p₂ f</td>
<td>CFKADS2043</td>
<td>24</td>
</tr>
<tr>
<td>Laegern 4</td>
<td>4</td>
<td>CO</td>
<td>0.006</td>
<td>p₂ f</td>
<td>CFKADS2043</td>
<td>24</td>
</tr>
<tr>
<td>Laegern 3</td>
<td>3</td>
<td>H₂O</td>
<td>0.05</td>
<td>NA</td>
<td>CFKADS2043</td>
<td>24</td>
</tr>
<tr>
<td>Fruebuel 1</td>
<td>1</td>
<td>CO₂\textsubscript{dry}</td>
<td>6</td>
<td>p₂ f</td>
<td>CFADS2256</td>
<td>20</td>
</tr>
<tr>
<td>Fruebuel 2</td>
<td>2</td>
<td>CH₄\textsubscript{dry}</td>
<td>0.006</td>
<td>p₂ f</td>
<td>CFADS2256</td>
<td>20</td>
</tr>
<tr>
<td>Fruebuel 3</td>
<td>3</td>
<td>H₂O</td>
<td>0.05</td>
<td>NA</td>
<td>CFADS2256</td>
<td>20</td>
</tr>
<tr>
<td>Beromünster 1</td>
<td>1</td>
<td>CO₂\textsubscript{dry}</td>
<td>6</td>
<td>p₂ f</td>
<td>CFKADS2038</td>
<td>24</td>
</tr>
<tr>
<td>Beromünster 2</td>
<td>2</td>
<td>CH₄\textsubscript{dry}</td>
<td>0.006</td>
<td>p₂ f</td>
<td>CFKADS2038</td>
<td>24</td>
</tr>
<tr>
<td>Beromünster 4</td>
<td>4</td>
<td>CO</td>
<td>0.006</td>
<td>p₂ f</td>
<td>CFKADS2038</td>
<td>24</td>
</tr>
<tr>
<td>Beromünster 3</td>
<td>3</td>
<td>H₂O</td>
<td>0.05</td>
<td>NA</td>
<td>CFKADS2038</td>
<td>24</td>
</tr>
<tr>
<td>Gimmiz 1</td>
<td>1</td>
<td>CO₂\textsubscript{dry}</td>
<td>6</td>
<td>p₂ f</td>
<td>CFADS2255</td>
<td>20</td>
</tr>
<tr>
<td>Gimmiz 2</td>
<td>2</td>
<td>CH₄\textsubscript{dry}</td>
<td>0.006</td>
<td>p₂ f</td>
<td>CFADS2255</td>
<td>20</td>
</tr>
<tr>
<td>Gimmiz 3</td>
<td>3</td>
<td>H₂O</td>
<td>0.05</td>
<td>NA</td>
<td>CFADS2255</td>
<td>20</td>
</tr>
<tr>
<td>Gimmiz 4</td>
<td>4</td>
<td>CO</td>
<td>0.006</td>
<td>p₂f\textsubscript{h}</td>
<td>HORIBA_A360</td>
<td>60</td>
</tr>
</tbody>
</table>

An overview of the main scripts is presented in Table A.3.

The executables in Table A.3 are called automatically as `cron` jobs on the GNU/Linux workstation ddm04326. The current configuration of the `cron` jobs is as follows:

```bash
# --- CarboCount Processing chain
R_PROFILE="/Documents/Conf_files/R/Rprofile.site"
LOGS="/remote2/CarboCountCH/logs"
SRC="/remote2/CarboCountCH/CarboCountDB/scripts"

# Update CarboCount Database
6 5 * * * $SRC/R/processRawData.R >> $LOGS/db_'date +\%F'.log 2>$&1

# Update Quicklooks
9 6-23 * * * $SRC/R/plotQuicklooks.R >> $LOGS/quicklooks_'date +\%F'.log 2>$&1

# operational calibration
12 6 * * 6 $SRC/R/runCalibration.R >> $LOGS/calibration_'date +\%F'.log 2>$&1

# Sync ftp
6 * * * $SRC/bash/sftp_sync.sh >> $LOGS/sftp_'date +\%F'.log 2>$&1

# Check if we are receiving the necessary data and if they are healthy
9 */3 * * * $SRC/R/checkRawData.R >> $LOGS/checkData_'date +\%F'.log 2>$&1

# Organize and rezip Bern data
14 4 * * 6 $SRC/bash/organizeBeromuenster.sh >> $LOGS/bern.dataOrg_'date +\%F'.log 2>$&1

# Organize and gzip Fruebuel Data
16 4 * * * $SRC/bash/organizeFruebuel.sh >> $LOGS/eth.dataOrg_'date +\%F'.log 2>$&1

# Gzip Laegern Data
10 4 * * * $SRC/bash/organizeLaegern.sh >> $LOGS/empa.dataOrg_'date +\%F'.log 2>$&1
```
Table A.3: The scripts use to control the execution of database organization, updates and evaluation.

<table>
<thead>
<tr>
<th>Script</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>processRawData.R</td>
<td>initialize processing; coordinates R-function: DatabaseControl</td>
</tr>
<tr>
<td>runCalibration.R</td>
<td>initialize calibration; coordinates R-function: CalibrateControl</td>
</tr>
<tr>
<td>plotQuicklooks.R</td>
<td>initialize plotting of the latest data; coordinates: quicklooks</td>
</tr>
<tr>
<td>checkRawData.R</td>
<td>coordinates emailNotify, which checks on data presence and size</td>
</tr>
<tr>
<td>sftp_sync.sh</td>
<td>get the data from the sftp</td>
</tr>
<tr>
<td>organizeBeromuenster.sh</td>
<td>organize and compress files retrieved from the sftp for Beromünster</td>
</tr>
<tr>
<td>organizeGimmiz.sh</td>
<td>organize and compress files retrieved from the sftp for Gimmiz</td>
</tr>
<tr>
<td>organizeFruebuel.sh</td>
<td>organize and compress files retrieved from the sftp for Früebüel</td>
</tr>
<tr>
<td>organizeLaegern.sh</td>
<td>organize and compress files from the sftp for Läger-Hochwacht</td>
</tr>
<tr>
<td>cleanup_Beromuenster.sh</td>
<td>remove old, archived files on sftp from Beromünster</td>
</tr>
<tr>
<td>cleanup_Gimmiz.sh</td>
<td>remove old, archived files on sftp from Gimmiz</td>
</tr>
<tr>
<td>cleanup_MeteoSchweiz.sh</td>
<td>remove old, archived files on sftp from MeteoSwiss</td>
</tr>
</tbody>
</table>

A.2.2 Traceability

Record of bad measurements as defined in Table 2.4 (>128) are kept within the site-wide CSV file, which has the site name, the time period and the reason for complete omission of measurement or calibration values. Complete absence of data for a day is also recorded. These records reside in this directory in the files:

- Site-BadMeasurements.csv
- Site-BadCalibrations.csv
- Site-NoMeasurementDays.csv

A.2.3 Processing Sequence to One-minute Averages

The processing procedure for greenhouse gas measurement data is done once for each site. In the below notation, the programming environment is noted first and a directional reference indicates a script (filename) being executed and the worker function being called, which calls other worker functions.

1. Data are (re-)compressed to a gzip-format.
   - sh: organizeBeromuenster.sh, organizeGimmiz.sh, organizeFruebuel.sh, organizeLaegern.sh

2. Initialized by the run-script processRawData.R, raw data are read from disk.
   - R: processRawData.R ↦ ingestRawData

3. Data in the valve transition period (nsecskip) are removed and measurement and calibration data are separately organized
   - R: ingestRawData ↦ organize_daily_data

4. Ambient measurements are checked for plausibility (see Table A.1).
   - R: ingestRawData ↦ organize_daily_data ↦ check_measured_signal

5. Ambient measurement data are summarized per minute and saved per day.
   - R: ingestRawData ↦ organize_daily_data ↦ average_daily_data_to_one_minute
6. Calibration data are saved in raw form per calibration.
   - R: ingestRawData ➔ save_standard_gas_measurements

7. Calibration procedure is initialized.
   - R: runCalibration.R ➔ calibrateData

8. Standard gas measurement data are summarized and surveyed and possibly flagged: updates or redoes the site's calibration database: site-CalibrationDatabase.csv
   - R: calibrateData ➔ update calibration database ➔ ingest_standard_gas_measurements check_basic ➔ check_device ➔ check_measured_signal
   - R: calibrateData ➔ plot_and.flag_cal.db
   - R: calibrateData ➔ flag_cal.from.db

9. Calibration parameters/coefficients are calculated: updates or redoes the site's calibration parameter database: site-CalibrationParameterDatabase.csv
   - R: calibrateData ➔ update_calibration_coefficient_database ➔ cal_3point, cal_2point, p3_o, p2_f, p1_z, etc.

10. Target measurements are calibrated: updates or redoes the site's target calibration database: site-TargetCalibrationDatabase.csv
    - R: calibrateData ➔ checkTargets ➔ apply_calibration_data

11. Measurement data are calibrated and flagged data (>16) are removed
    - R: calibrateData ➔ check_extreme_signal
    - R: calibrateData ➔ apply_calibration_data
    - R: calibrateData ➔ insert_target_uncertainty

A.2.4 Automatic application of flagging system to ambient and calibration measurements

The ambient water concentration, and the carbonic gas concentrations also have lower limits. These constraints are summarized in Table A.4 and are removed and the abnormalities are saved in the Site-Bad*.csv files, depending on the operation mode.

A.2.5 Manual application of flagging system to ambient and calibration measurements

Where the R run scripts reside (/remote2/CarboCountCH/CarboCountDB/scripts/R/), there is also an interactive R-script with the names manual.data.inspection.R, where the averaged ambient measurement values are inspected and code therein records anomalies in: Site-BadMeasurements.csv.
Table A.4: The limits for standard gas and ambient greenhouse gas measurements. For exact numbers, please see Table A.1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Limits</th>
<th>Unit</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>H2O</td>
<td>&lt; 0.06</td>
<td>%</td>
<td>Raw trace gas concentration measurements.</td>
</tr>
<tr>
<td>CO2_dry</td>
<td>&lt; 6</td>
<td>ppm</td>
<td></td>
</tr>
<tr>
<td>CO</td>
<td>&lt; 0.006</td>
<td>ppm</td>
<td></td>
</tr>
<tr>
<td>CH4_dry</td>
<td>&lt; 0.006</td>
<td>ppm</td>
<td></td>
</tr>
</tbody>
</table>

A.2.6 The R-package ccchDataProc

A custom R-package was written for this project and is well-documented. Several programmatic ideas guided the development of this package. Except for the scripts mentioned above as run scripts, the focus has been on functional programming. The local paths for data input and output as well as time-dependent site descriptions (site.info) are held within the R-data file specific to this package data(ccchData). There have been no package-specific classes defined. The section below describes the functions that can be found in the R/ sub-directory of the package as R-source files. Often the main functions mentioned reside in a file with the same name.

A.2.6.1 R-functions for processing data

In order to run code and process data, one needs to source the R-file config.ccchDataProc.R for the below code to work OR install and load R-package ccchDataProc with library(ccchDataProc) as well as the data from the package data(ccchData). See the R-script processRawData.R for an example. The R-help is thorough.

General code

- config.ccchDataProc.R script with various site-specific data and reads in all below functions
- miscFunctions.R many miscellaneous important functions from reading PICARRO files to lengthening vectors.
- retrieve.site.information.R functions to retrieve site-specific data such as:
  - check.site.info updates the site.info data.frame which contains information regarding changes in valve position etc.
  - check.device.info updates the site.device.info data.frame which contains info regarding the measurement devices, and gas-specific calibration strategy/routine.
- tools.flagging.R data quality assessment and recording functions
- getFileInfo retrieve the file’s information along with the time stamp, which is deduced from the file name.
- bern.data.processing handle the Bernese data formats and problems

Plotting

- quicklooks for plotting the default quicklooks for the CarboCount CH project.
- interactive.plots.R contains functions for plotting the measurement data.
- plot.cal.databases.R contains functions for plotting the calibration data.
Diagnostics

- **emailNotify.dat.size.and.presence** checks on the presence and size of raw PICARRO files being received hourly from sites. This is only true for Fruebuel and Lagern-Hochwacht, and of course only checks for those sites. The run script is in the R directory.

- **Gap.check** checks whether the averaged data correspond to the available raw data.

Higher Time Aggregates and Associated Uncertainty

- **tools.TS.R** contains functions such as: *Summary.gases.meteo et al.* which aggregate data over arbitrary periods.

- **ingestRawData** This function initially processes raw data for each site, taking care of averaging of measurement data and organizing calibration data.

- **organize_daily_data** takes the nsecskip into account and removes valve transition data accordingly

- **average_daily_data.to_one_minute** function for averaging over one minute intervals. The functions in the picarro.summary.R R-script e.g.

- **picarro.meas.summary et al.** are used to calculate the means and uncertainties while accounting for the repetition of the data within PICARRO *.dat files.

- **save_standard_gas_measurements** takes the calibration data and saves an accordingly named file for each calibration type.

- **calibrateData** This function coordinates summary of the calibration data, application to target (targets_check) and ambient measurements.

- **tools.calibration.R** contains functions to find span (high and low) and target gas measurements, as well and calibration functions for two-point calibrations etc. handling each site, situation and trace gas with zero-intercept and offset calibration capabilities.

- **cal_3point** span free-intercept, zero-intercept and offset calibration.

- **cal_2point** two-point free-intercept and zero-intercept calibration.

- **cal_1point** zero-intercept calibration.

- **update_calibration_database** reads in (new) calibration data for each site.

- **ingest_standard_gas_measurements** process raw calibration data, output is: mean, uncertainty, standard deviation, number of measurements.

- **plot.and.flag.cal.db** plots and allows for manual flagging (their record) of standard gas measurements.

- **flag.cal.from.db** flags calibrations based upon the sites calibration database.

- **update_calibration_coefficient_database** compiles and update the calibration parameter data for each site.

- **targets_check** apply the calibration scheme and data to target calibrations.

- **get.cal.parameters** which retrieves time-dependent calibration parameters for calibration of a certain day from the calibration databases.
• **apply_calibration_data** apply calibration data to target data.

• **get.targ.parameters** which retrieves time-dependent calibration parameters for target calibration of a certain day from the calibration databases.

• **apply_calibration_data** apply calibration data to measurement data.

• **insert_target_uncertainty** insert the target uncertainty for a certain period

### A.2.6.2 Calibration Implementation Details

A few core R-functions (cal_1point, cal_2point cal_3point) implement the above methodology given different arguments and configured with time-dependent tabular information (e.g. Table A.1) using the R-function, which is designated by "Code", and described in Table A.5.
### A.2. Data Processing and Management

#### Table A.5: The calibration strategies used in CarboCount CH and respective R-function names as well as the standard gas types.

<table>
<thead>
<tr>
<th>Type</th>
<th>Code</th>
<th>Bottles</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-point zero intercept</td>
<td>p₁z</td>
<td>work</td>
<td>The slope is calculated from the <em>ex situ</em> determined and measured concentration ratio for a standard gas and the uncertainty of the slope is calculated using the derivation of the Gaussian uncertainty propagation principle. The intercept is forced through zero, without uncertainty.</td>
</tr>
<tr>
<td>1-point zero intercept</td>
<td>p₁z₁</td>
<td>low</td>
<td>Same as above, but for low standard gas.</td>
</tr>
<tr>
<td>2-point free intercept</td>
<td>p₂f</td>
<td>high, low</td>
<td>The slope and intercept are solved for analytically and their uncertainties are directly calculated using the derivation of the Gaussian uncertainty propagation principle.</td>
</tr>
<tr>
<td>2-point free intercept</td>
<td>p₂fₜ</td>
<td>COₙₜ, COₙₙ</td>
<td>Same as above, but for HORIBA to evaluate zero-level information.</td>
</tr>
<tr>
<td>2-point zero intercept</td>
<td>p₂z</td>
<td>high, low</td>
<td>With a weighted total least square regression, the slope and intercept along with their uncertainties as well as the their covarariance are directly calculated. The intercept is forced through zero, without uncertainty.</td>
</tr>
<tr>
<td>3-point free intercept</td>
<td>p₃f</td>
<td>high, work, low</td>
<td>With a weighted total least square regression, the slope and intercept along with their uncertainties as well as the their covarariance are directly calculated.</td>
</tr>
<tr>
<td>3-point zero intercept</td>
<td>p₃z</td>
<td>high, work, low</td>
<td>With a weighted total least square regression, the slope and intercept along with their uncertainties as well as the their covarariance are directly calculated. The intercept is forced through zero, without uncertainty.</td>
</tr>
<tr>
<td>3-point offset</td>
<td>p₃o</td>
<td>high, work, low</td>
<td>The slope and intercept is initially calculated as a 2-point free-intercept (p₂z) from high and low calibrations. The intercept is then adjusted between span calibrations.</td>
</tr>
</tbody>
</table>
List of Tables

2.1 Location and instrumentation of the measurement sites of the SNF Sinergia CarboCount CH Project. ......................................................... 20

2.2 Approximate reference gas mole fractions of aluminum bottles. Mole fractions have units of $\mu$mol/mol$^{-1}$ mole fraction or molar parts per million (ppm). ........................................... 20

2.3 Parts of Läger-Hochwacht measurement system which was mostly replicated at Früebüel. The legend indicates unapparent parts in Figure 2.1. The lower half contains specific Swagelok® parts. ......................................................... 23

2.4 Flag table for CarboCount CH measurement data. ................................................................. 31

2.5 Root mean square error (in ppm) between known and calibrated target reference gas mole fractions during their period of measurement (see Figure 2.5). ........................................ 31

3.1 Details of the four measurement sites of the CarboCount CH network. From left to right: the site name, the site code, measurement commencement date, the measurement height(s), measured trace gases, the site’s altitude (m a.s.l.), and the geographic site locations. ........................................... 43

3.2 Simulation characteristics for the four measurement sites of the CarboCount CH network. Listed from left to right are the FLEXPART-COSMO particle release heights (above model ground level), the “true” site altitudes (m a.s.l.), smoothed COSMO numerical weather prediction model’s (∼4km$^2$) site altitude, and the geographic site locations. ........................................... 44

4.1 Simulation characteristics for two observation sites of the CarboCount CH network. Listed from left to right are observation heights (m above ground level), FLEXPART-COSMO particle release heights (m above model ground level), the “true” site altitudes (m above sea level), smoothed COSMO numerical weather prediction model’s (∼4km$^2$) site altitude, and the geographic site locations. ........................................... 65

4.2 An overview of the model and observation based CO$_2$ component estimates. All observation-based estimates (obs*) calculate the CO$_2$ background with a 45-day REBS, and translate CO above a similar CO background estimate with the designated $\beta$. All modeled estimates were calculated with FLEXPART-COSMO and the data product listed. ........................................... 67

4.3 Sensitivity of the inverse ratios $R_{obs}$ ($\equiv \beta_{obs}^{-1}$) to the choice of observations used to determine the background signal, and to the choice of width of local regression window. Also shown are model-based ratios $R_{mod}$. The units of $R$ are ppb CO/ppm CO$_2$. The uncertainty ($\pm$) of $R$ is determined as $2\sigma$ of the slope of the total weighted least squares regression. ........................................... 75
4.4 Summary of observed $R$'s found in previous studies. The upper portion of the table displays long-term observation results, and the lower half of the table displays observation campaign results. $\text{CO}_A/\text{CO}_2 R$ refers to ratios calculated from continuous CO$_2$ and CO observations above background, analogous to this study. $\text{CO}_A/\text{CO}_2,\text{FF}$ indicates fossil fuel CO$_2$ ($\text{CO}_2,\text{FF}$) calculated from $^{14}$C [see Levin et al., 2003]. The information used for the method is presented as the apparent ratio calculation, background, and the metric shown. The units of $R$ are ppb CO/ppm CO$_2$.

A.1 The latest table (site.info) from 2014-08-21 at 09:00:00 UTC, Ruediger Schanda changed the CO high bottle at Gimmiz. This table is written out by this org-mode (emacs) document with R as SiteInfo-2014-08-21-090000.csv in the directory where this file resides. NA stands for ‘not available’.

A.2 The latest measurement device and calibration information from 2014-04-29 at 09:38:00, when the normal device at Beromünster was put back into service, replacing the ersatz G2311-f. This table is queried when calibration parameters are calculated (defining the calibration type) and raw data are checked to see whether they are feasible (e.g. is CO$_2$.dry $>$ 67%). For example, this table is written out by this org-mode document with R as SiteDeviceInfo-2014-04-29-093800.csv in the directory where this file resides. NA stands for ‘not available’.

A.3 The scripts use to control the execution of database organization, updates and evaluation.

A.4 The limits for standard gas and ambient greenhouse gas measurements. For exact numbers, please see Table A.1.

A.5 The calibration strategies used in CarboCount CH and respective R-function names as well as the standard gas types.
List of Figures

1.1 The global carbon cycle depicted as pools and fluxes. Arrows and their annotations denote annual carbon fluxes (PgC yr$^{-1}$). Boxes represent the carbon pools (PgC). Preindustrial flux and pool magnitudes are black and additional anthropogenic fluxes and pools are red. Figure is slightly modified from Ciais et al. [2013].

1.2 Partitioning of annual anthropogenic CO$_2$ emissions from 1750 to 2011 (positive) between the three major sinks: atmosphere, ocean, and land. Figure is slightly modified from Ciais et al. [2013].

1.3 Range of accumulated (PgC) and annual carbon flux (PgC yr$^{-1}$) from the atmosphere into the ocean or land surface as estimated by land surface models, which are driven by CO$_2$ emissions, and simulate the feedbacks between the carbon cycle and climate differently. The figure and simulations are from the fifth phase of the Coupled Model Intercomparison Project [CMIP5; Friedlingstein et al., 2014].

1.4 CO$_2$ time series measured at Mauna Loa, Hawai’i (MLO) and the South Pole Antarctica (SPO) by the Scripps Institute of Oceanography [Keeling et al., 2001].

1.5 Vertical, zonal profiles of CO$_2$ observations from a Maine to North Dakota and c from Idaho to Maine, USA, taken during the COBRA-2000 intense measurement campaign. From Gerbig et al. [2003a].

1.6 Retrievals of biospheric surface carbon fluxes constraining seasonal sets of biosphere model parameters (Post Params) and seasonal flux inventories (Post Pixels) compared with “known” biospheric fluxes (Prior). Taken from Meesters et al. [2012].

1.7 Schematic representation of the fundamental CarboCount CH project elements: tower observations, carbon fluxes (bidirectional arrows), and transport models (unidirectional arrows). Figure kindly provided by the Graphics Department, Empa.

2.1 Airflow schematic at Lägern-Hochwacht.

2.2 Left: Calibration with offset $a$ and slope $b$. Standard errors of the calibration measurements are indicated by the horizontal arrows. Right: Similar to the left panel but the regression is forced through zero. Additional reference gas measurements may be included in both cases.

2.3 Example sequence with one LOW and HIGH reference gas measurements between ambient measurements MEAS.

2.4 Schematic of temporal interpolation (top) or temporal averaging (bottom) of calibration coefficients from “span” calibrations binning the targeted processing time $t_{int}$. 
2.5 Target gas calibration results at the CarboCount CH sites. Individual differences between known and calibrated target gas molar ratios are plotted, with independent analytical and target uncertainty bands (±). ................................................................. 32

2.6 Atmospheric carbon measurements (CO₂, CH₄, & CO) during afternoon (1200-1500 UTC, 1300-1600 LT) at the CarboCount CH sites. The Beromünster data are from the highest sampling height (212 m). ........................................................... 34

2.7 Seasonal average daily cycles of observed atmospheric carbon mole fractions from the CarboCount CH sites. Uncertainty bands correspond to ±1σ at the respective time of day. Time zone is UTC. ................................................................. 35

3.1 An overview of CarboCount CH measurement site locations within Switzerland: Beromünster (BEO), Früebüel (FRU), Gimmiz (GIM), and Läger-Hochwacht (LAE). The sites are concentrated along the Swiss Plateau. The measurement heights and locations are listed in Table 3.1. Also shown are other sites with greenhouse gas concentration or flux measurements that complement the network. These include the sites of the Swiss FluxNet, the high Alpine research station Jungfraujoch, and sites of the Swiss air pollution monitoring network NABEL (National Air Pollution Monitoring Network). ...................................................... 41

3.2 Site surroundings including land use (first column), topography (second column), and Google aerial photo (third column), with Beromünster (a–c) in the first row, and Gimmiz (d–f) in the second row. The land use (a and d) is based on CORINE 2006 land cover classes color coded as follows – urban: red; food croplands: beige; evergreen forest: green; deciduous forest: light green; pasture: light brown; agroforestry areas: tan. Cyan contour lines in the topography panels (b and e) denote the COSMO-2 model topography. ...................................................... 47

3.3 Similar to Fig. 3.2 with Früebüel (a–c) in the first row and Läger-Hochwacht (d–f) in the second row. ................................................................. 48

3.4 Wind roses at the four measurement sites during the study period (1 March 2013–28 February 2014) for observed (first column) and simulated horizontal wind at two different model heights: at the height of the measurement a.m.g.l. (Model, second column), and at the true height of the measurement a.s.l. (True, third column). The wind roses display the wind speed probability distribution split into incident 30° wind direction bins. Wind from the north is upward and circular lines demarcate graduating 5th percentiles. Labels above each panel show the height above ground for the measurements (first column) and height above the COSMO-2 model ground for the simulated data (second and third columns). ................................................................. 50

3.5 Mean summer (June–August 2013) diurnal cycle of measured and simulated local meteorology at the sites Beromünster and Gimmiz: (a and b) temperature, (c and d) specific humidity (Sp. Hum.), and (e and f) wind speed (W. S.). Also shown are mean diurnal cycles of measured (g and h) regional CO₂ signals (ΔCO₂), and (i and j) regional CH₄ signals (ΔCH₄). The measurement and simulation heights above ground are listed in the figure legends. Simulated meteorology is shown for two different heights, the height of the measurement a.m.g.l. (Model, dark blue), and the simulation height a.m.g.l., which corresponds to the “true” measurement altitude a.s.l. (True, light blue). The time zone in Switzerland is central European time (CET or UTC +1). ................................................................. 52

3.6 Similar to Fig. 3.5, the mean diurnal cycles during winter (December 2013–February 2014) at the sites Beromünster and Gimmiz. ................................................................. 53
3.7 Similar to Fig. 3.5, the mean diurnal cycles during summer (June–August 2013) at the sites Früebüel and Lägern-Hochwacht. The Früebüel meteorological measurements were made at 2 m a.g.l. .......................... 54

3.8 Similar to Fig. 3.5, mean diurnal cycles during winter (December 2013–February 2014) at the sites Früebüel and Lägern-Hochwacht. The Früebüel meteorological measurements were made at 2 m a.g.l. .......................... 55

3.9 Monthly (YYYYMM) mean nighttime (00:00–03:00 UTC; a, c, and e) and daytime (12:00–15:00 UTC; b, d, and f) measured regional carbon dioxide signals, $\Delta CO_2$, measured regional methane signals, $\Delta CH_4$, and simulated monthly total surface sensitivities, $T_T$ (Eq. 3.3.1), during the study's time period (1 March 2013–28 February 2014). Regional signals are computed as the measured concentration minus a background concentration estimate from Jungfraujoch, and total surface sensitivities provide a linear estimate of how much arriving air parcels at a measurement site have been in contact with the model domain’s surface. .................. 56

3.10 Monthly (YYYYMM) land cover type (LCT) contributions $C_{LCT}$ (Eq. 3.3.2) for Beromünster (a), Früebüel (b), Gimmiz (c), and Lägern-Hochwacht (d), calculated as the pixel-wise multiplication of the monthly mean surface sensitivities with the respective LCT fraction and divided by the monthly averaged total surface sensitivities. .................. 57

3.11 Surface sensitivities as a function of distance from the measurement site position $T_k$ (Eq. 3.3.3). Lines are color coded according to measurement site (Beromünster: dark blue, Früebüel: orange, Gimmiz: light blue, Lägern-Hochwacht: red). The vertical dotted line is the radius at which the cumulative surface sensitivity starting from the measurement site’s position reaches 50% of the simulation domain total, $\tau_{50}$. (a) Summer (June–August 2013), (b) winter (December 2013–February 2014), and (c) and (d) summer afternoon (15:00 UTC) and at nighttime (03:00 UTC), respectively. Please note the logarithmic y axis and that, during winter, for Beromünster and Lägern-Hochwacht the 50% vertical dotted lines overlap. The site-specific particle release heights are listed in Table 3.2. Local time is central European time (CET or UTC +1). .................. 58

3.12 Area of surface influence (Eq. 3.3.5) defined as the isoline at the site-dependent value $\tau_{50}$ encompassing 50% of the total mean surface sensitivities. Lines are color coded according to measurement site – Beromünster: dark blue, Früebüel: orange, Gimmiz: light blue, Lägern-Hochwacht: red. (a) Summer (June–August, 2013), (b) winter (December 2013–February 2014), and (c) and (d) summer (June–August 2013) in the afternoon (15:00 UTC) and at nighttime (03:00 UTC), respectively. Local time is central European time (CET or UTC +1). .................. 59

4.1 Simulation domains of this study. The COSMO-7 represents the driving meteorology. The west European and Switzerland domains comprise the areas where surface sensitivity and flux influence is calculated for the past 4 days to simulate regional signals. Outside these temporal and spatial domains the initial concentration is taken as the background signal. .................. 69

4.2 Observed $CO_2$ concentrations (A), observation-based (obs1) and FLEXPART-COSMO-modeled (mod1) $CO_2$ background (B), anthropogenic (C) and biospheric (D) components at Beromünster during 2013. Also shown in (A) is the sum of all simulated components. For an overview of the settings for obs1 and mod1 see Table 4.2. .................. 71

4.3 Same as Fig. 4.2 but at the Lägern-Hochwacht site. .................. 72
4.4 CO₂ (panels A–B) & CO (panels C–D) measured concentrations (black and gray) and “robust estimate of baseline signal” (REBS) estimates (red and orange) at Beromünster, Lägern-Hochwacht, and Jungfraujoch (JFJ) during 2013. The REBS background estimates are calculated with a 45-day local regression window. ............................ 73

4.5 Modeled and measured CO₂ and CO regional signals at Beromünster and Lägern-Hochwacht, colored according to season. Panel A: modeled CO₂,A and CO,A at Beromünster. The slope of the regression line corresponds to \( \beta_{\text{mod}} \) of method mod1. Panel B: CO₂,R and CO,A regional signals above a background signal from Jungfraujoch. The slope of the regression line is calculated using only wintertime regional signals and corresponds to \( \beta_{\text{obs}} \) of method obs1. Panel C: the same is shown as in panel B except using background estimates from the target site Beromünster (method obs5). Panels D-F: the same as panels A–C shown with regional signals from Lägern-Hochwacht. .................................................. 75

4.6 Late winter- and springtime pollution events during which neither observation based nor modeled estimates explain the observed CO₂ at Beromünster and Lägern-Hochwacht. Modeled and observed regional CO : CO₂ ratios above a threshold which denotes an isoline which includes 90 % of the cumulative sum of surface sensitivities [see Oney et al., 2015]. Individual regional signals were spatially disaggregated according to Stohl [1996]. .............................. 78

4.7 Afternoon (1200–1500 UTC) biospheric CO₂ signals at Beromünster and Lägern-Hochwacht during 2013. The modeled (mod1) and observation-based (obs1) biospheric signals (CO₂,B) are also shown in panel D of Figs. 4.2 & 4.3. The uncertainty (gray) enveloping the residual biospheric signal (obs1) accounts for the uncertainty introduced by the observation based background and anthropogenic CO₂ signals. ................................. 80

4.8 Comparison of biospheric CO₂ signals (CO₂,B) at Beromünster (panel A) and Lägern-Hochwacht (panel B) during the period of 2013-01 – 2013-03. ................................................................. 81

4.9 Comparison of the statistical distributions (box and violin [kernel density] plots) of afternoon (1200–1500 UTC) CO₂ biospheric signals at Beromünster (panels A–D) and Lägern-Hochwacht (panels E–H) during 2013, summarized by season for each method (Table 4.2). The mean of each distribution is marked by a diamond. ................................................. 82

4.10 Observed afternoon (1200–1500 UTC) biospheric CO₂ signals (obs1) along with temperature (average of past 24 hours), photosynthetically active radiation (PAR) accumulated over the past 24 hours, as well as precipitation accumulated over the previous 21 days (as a proxy of soil moisture), during the main growing season (01 May–01 September) of 2013 interpolated from COSMO-2 analysis fields to the observation site positions, Beromünster and Lägern-Hochwacht at 250 m above model ground level. Shaded areas demarcate periods during which the average temperature of the preceding 24 hours was > 20° C. ................................. 84

4.11 Response of observed afternoon (1200–1500 UTC) biospheric CO₂ signals (obs1) to modeled (described in Fig. 4.10) PAR, accumulated precipitation, and average temperature at both Beromünster and Lägern-Hochwacht during the growing season (01 May–01 September) of 2013. We narrowed our investigation to convective meteorological situations according to the categorization by Weusthoff [2011]. The blue line corresponds to a generalized additive model binned by the 95% confidence interval. ................................. 85
5.1 Distributions of observed afternoon (1200–1500 UTC) biospheric CO$_2$ signals (obs1) and observed average temperature (of the preceding 24 hours) at both Beromünster and Lägern-Hochwacht during the growing seasons (01 May–01 September) of 2013–2015. Observations shown are only during convective meteorological situations according to the categorization by Weusthoff [2011]. ................................................................. 92

5.2 Response of observed afternoon (1200–1500 UTC) biospheric CO$_2$ signals (obs1) and observed temperature averaged of the preceding 24 hours at both Beromünster and Lägern-Hochwacht during the growing seasons (01 May–01 September) of 2013–2015. Observations shown are only during convective meteorological situations according to the categorization by Weusthoff [2011]. ................................................................. 93
Bibliography


Raschendorfer, M., New features of the common turbulence parameterization for COSMO and ICON, 2016.


Zellweger, C., J. Forrer, P. Hofer, S. Nyeki, B. Schwarzenbach, E. Weingartner, M. Ammann, and U. Baltensperger, Partitioning of reactive nitrogen (NOy) and dependence on meteorological conditions in the lower free troposphere, Atmospheric Chemistry and Physics, 3, 779–796, 2003.


Curriculum vitae

Brian Johannes Oney
Male, born Nov. 9th 1984, in Carlsbad, NM, USA
Email: brian.j.oney@gmail.com

Education

04/12–01/16 Ph.D. at Empa, Laboratory for Air Pollution / Env. Technology, Dübendorf, Switzerland, under supervision of Dr. Dominik Brunner and Prof. Dr. Nicolas Gruber – Center for Climate Systems Modeling, ETH Zurich
10/08–10/11 Master of Science in Global Change Ecology, Thesis supervised by Björn Reineking and Jürgen Kreyling – University of Bayreuth
9/03–5/07 Bachelor of Arts in German Studies cum laude – Weber State University (WSU)
9/03–5/07 Bachelor of Science in Zoology with Chemistry Minor cum laude – WSU

Literary Works

Oney, B. J., Toward using atmospheric carbon dioxide observations to estimate the biospheric carbon flux of the Swiss Plateau, Ph. D., ETH Zurich, Zurich, Switzerland, doi:10.3929/ethz-a-010677958, 2016.
Thanks

I would above all like to thank my advisor Dominik Brunner for his insight, patience, and tireless support. Without his support, most components for this dissertation would not have come to be. Stephan Henne provided code, patience, rigor, and humor, without which many of the modeling goals and CarboCount would have been wishful thinking. I greatly appreciate the time, and wisdom of my doctoral supervisor Niki Gruber. Without his exemplary guidance, I would not have learned a delicate balance between critical review and acceptance that provides fundament for progress and collaboration. Thanks to Lukas Emmenegger for helping to keep me on track. Thank you very much to Christoph Gerbig for kindly agreeing to review my dissertation. Thank you Nina Buchmann for sovereignly supervising my thesis defense and enriching its discussion.

I greatly appreciate the support of and fruitful discussions with Christoph Zellweger and Martin Steinbacher. Without their guidance and experience in measurement technique, it is possible that the measurement system at Lägern-Hochwacht or at Früebüel would not have worked. On the contrary, these systems functioned so well, that they were often forgotten, which left time for modeling and writing papers. Furthermore, their willingness to help encouraged me to ask and learn regardless how elementary the question. Martin Vollmer was instrumental in both the installation at Lägern-Hochwacht and the filling of the 21 aluminum bottles for the CarboCount CH project. His experience and detailed attention helped a great deal with initiation of the project.

Within CarboCount CH, my thanks is due to Markus Leuenberger, Ece Satar, Tesfaye Berhanu, René Bleisch, and especially to Rüdiger Schanda of the University of Bern for being patient with me. I hope the Beromünster and Gimmiz site run well for years to come.

Thank you to Erich Graf and Thomas Lehmann of Skyguide for the unrelenting and quick support the set-up and maintenance of the Lägern-Hochwacht measurement site. Have fun and be safe on the towers!

Thank you to my two fellows for the psychological support, well-meant insults, and bad jokes. Simon Eyer and Fabian Schoenenberger gave misery company à la suisse and hopefully will soon find release from the “joys” of being a PhD student at Empa. Thank you also to another fellow, Pascal Butti, for the philosophical walks and insight into music culture.

Thank you to Eliza Harris and Franz Holzknecht, Jana Jagerska, Markus Mangold, and Benjamin and Diana Wolf for the many wonderful evenings playing Schafkopf and Jassen. Gerne wieder! Thank you to the float crews for sharing time on the Limmat: Erkan Ibraim, Florian Arfeuille, Antoine Berchet, Gianluca Mussetti. To Julien Anet, Gianluca, Florian, and Fabian, hopefully we can get some ski tours in this winter, and more river floats next summer!

Thank you Carole Delemont for initiating ninepins (Chegle). Thank you Robert Gehrig, Joachim Mohn, and Christoph Hüglin for the suspense. Thanks to the rest for good sportsmanship and losing gracefully (except Lukas). I hope ninepins becomes tradition in this lab.

Thank you Béla Tuzson for the philosophical discussions about culture, politics, and science. Thank you
Stefan Bugmann for the beets and smiles. I know you will enjoy helping others after Empa. Thanks to new and gone office colleagues for the beers and laughs: Christoph Popp, Christoph Knote, Eirini Boleti, Yvo Strebel, Morten Hundt, Wilhelm Gutjahr, and Rebecca Hiller.

Thank you to Carl Beierkühnlein for instrumenting the Global Change Ecology program at the University of Bayreuth for motivating me to study policy relevant environmental science. Thank you to my master’s thesis advisors Björn Reineking and Jürgen Kreyling for the patience and support of my first dive into the analysis of environmental data.

Thanks to Tim Besser for looking over my German and for keeping my thoughts on sustainability grounded in reality.

Of course, great appreciation goes to my parents and little sister for their perspective, support, and love. I’ll come home one of these days.

Without my wonderful girlfriend Sia Gosheva, life would be less exciting and less complete. Furthermore, her detailed comments and proofreading of this thesis most certainly improved its quality. I appreciate her patience, support, and love far beyond my ability to express this gratitude.