Chapter 3

Atmospheric Moisture Sources, Paths, and the Quantitative Importance to the Eastern Asian Monsoon Region

A Lagrangian model [Flexible Particle dispersion model (FLEXPART)] was used to calculate the back trajectories of air parcels residing over the East Asian monsoon region (EAM) for a 4-yr period (2009–12). To detect the moisture source-sink relationships to the EAM, the moisture budgets were evaluated by diagnosing the changes of specific humidity along the trajectories. A circulation constraint method was proposed to define the moisture sources of the EAM, to quantify their importance, to depict the moisture transport processes, and to reveal the fate of the moisture from different sources. The results indicated that in winter the largest airmass inflow is through the dry westerlies, but they do not form net precipitation. The much smaller contribution of the tropical oceans is more relevant to winter precipitation. In summer, the main contribution was through the southwest monsoon, with a mean specific humidity of 9.8 g kg$^{-1}$ when entering the EAM, providing more than 40% of the moisture to the EAM and making the southwest monsoon the most humid and abundant moisture source of the EAM. Local evaporation plays an important role as a moisture source for the EAM both in summer and winter.
3.1 Introduction

China is the world’s most populous country, feeding 22% of the world’s population with only 7% of the world’s arable land (Piao and Coauthors, 2010). About 90% of the country’s population and gross domestic product are concentrated in a much smaller region, which has a remarkably monsoonal climate, the East Asian monsoon region (EAM; 20°–40°N, 101°–121°E; Fig. 3.1). However, this densely populated area is prone to both floods and droughts as a result of uneven spatiotemporal distribution of precipitation (Li et al., 2012a). The East Asian monsoon is characterized by a wet season and southerly flow in summer and by a dry, cold, northerly flow in winter (Christensen and Coauthors, 2014). It accounts for 40%–50% (60%–70%) of the annual total precipitation in southern (northern) China (Zhou et al., 2009). Extreme hydrological events (i.e., floods and droughts) are associated with extreme excess or deficit of precipitation. Over the EAM, the portion of total precipitation derived from extreme events increased during the past few decades at the expense of more moderate events (Wang et al., 2012; Xu, 2013).

Extreme precipitation (95th percentile) typically accounts for 30%–40% of annual totals; in past decades, this quantity has mainly increased in southern China, but decreased in northern China (Zhai et al., 2005). The occurrence and frequency of precipitation events depends, among other factors, on the interplay between available moisture in the atmosphere and the dynamics of convection (Trenberth, 2011). It is therefore important to consider the regional water system as a combined land and atmosphere system in which the water budgets within a specific volume or reservoir play an important role (Dirmeyer and Brubaker, 1999). In other words, where does the moisture that generates precipitation in the EAM come from?

Precipitation that falls in a region can originate from three sources: local evaporation, moisture advected into the region by wind, and moisture that is already present in the atmosphere. Over longer periods, the last one contributes little, and thus the main sources are expected to be local evaporation and advection (Brubaker et al., 1993; Trenberth, 1999a). Trenberth et al. (2003) suggested
that the moisture supply for moderate to heavy precipitation locally relies heav-
ily on advective sources of moisture, originating from distances of about 3–5
times the radius of the precipitation region. From this perspective, local precip-
itation greatly depends on the transport of moisture from other regions by the
atmosphere. It is thus of great importance to consider the sources and variabil-
ity of the advected moisture when considering causes of hydrological extremes
(Trenberth, 1999a; Nieto et al., 2006b). Furthermore, by analyzing the variabil-
ity in moisture source regions (e.g., strength and distribution), in the context of
long-term climate change, the impact on moisture availability and subsequent
precipitation variability over target regions can be better understood.

Several approaches have been used to estimate the source regions of mois-
ture. Gimeno et al. (2012) summarized these into three principal methods, that
is, analytical or box models, numerical water vapor tracers, and physical water
vapor tracers (isotopes). The reader is referred to this work for a complete re-
view of the theory and comparisons among these approaches. The numerical
water vapor tracer model of Stohl and James (2004, 2005) obtains trajectory in-
formation from a particle dispersion model, and the only input to the moisture
diagnostics is the change in specific humidity with time (Gimeno et al., 2012).
This approach has been found to be very useful and is applied in many related
studies (e.g. Spracklen et al., 2012; Drumond et al., 2011).

Previous studies have also tried to quantify the relative importance of differ-
ett moisture source regions based on the numerical water vapor tracer methods.
Because an air parcel may undergo multiple cycles of evaporation and precipita-
tion during the backward calculation period, even if an area is a strong moisture
source, there is a possibility that only limited moisture originating from the area
could arrive in the target regions (Sodemann et al., 2008; Gustafsson et al., 2010;
Sun and Wang, 2014). Sodemann et al. (2008) proposed a combined method to
identify moisture sources and to evaluate the relevance of the identified sources
by giving a definition of the so-called uptake sector [e.g., Fig. 8 from Sodemann
et al. (2008)]. This approach was followed by Martius et al. (2013) for the iden-
tification of moisture sources in the Pakistan flood in July 2010. Recently, Sun
and Wang (2014, 2015) presented a modified version of this approach in order
to calculate the total contribution of a source region to the total precipitation in
the target region. These studies made it possible to calculate the moisture con-
tribution from different source regions quantitatively. However, the definition
of an uptake sector remains somewhat arbitrary. Thus, the limits of the source
region for a certain area given by different approaches may differ widely. Im-
portantly, the source–sink relationship to the target area varies at different stages
of the back tracking (e.g., the source–sink evolution in section 3.3). The defined
uptake sector is not necessarily the constant moisture source during the whole
calculation period.

Numerous previous studies, mainly in application to air pollution problems,
exist using cluster analysis for trajectories (e.g. Moody and Samson, 1989, and
many others). Simple approaches have been used to group trajectories based on
wind direction (e.g. Miller et al., 1993). However, these approaches are also par-
tially subjective in the sense that the trajectories were grouped into fixed, user-
deﬁned clusters (Hondula et al., 2010). More objective approaches tend to com-
pute the similarities by distance-based methods, such as by $k$-means algorithms,
which is accomplished by computing the Euclidean distances of trajectories to
their closest representatives (e.g. Dorling et al., 1992, and many others).

However, the distance-based methods have the following challenges. First,
trajectory simulations tend to use higher spatiotemporal resolutions and release
a larger number of particles. Thus, the dimension of the data to cluster is high
and the number of the data is massive. In this case, distance-based approaches
would be computationally expensive. Second, the $k$-means algorithm does not
always work well when the clusters are of arbitrary shape because it implicitly
assumes a spherical shape for the cluster. Third, depending on the initializa-
tion criteria, it is possible for the distance-based algorithms to create suboptimal
clusters even though these algorithms are robust to the choice of initialization
(Aggarwal, 2015). Fourth, since cluster analysis is an unsupervised problem, it is
difficult to evaluate the quality of such algorithms. Consequently, the quality of
the clusters would also be difficult to evaluate in many real scenarios.

Considering these challenges of cluster analysis for trajectories, a potential
solution may rely on a better utilization of the prior knowledge of the general
circulation. In the circulation constraint method we propose in section 3.2, the criteria are initialized based on the traditional understandings of the airflows over the EAM. Importantly, supervision to the clustering processes has been provided based on the circulation features over the EAM, and visual feedbacks have specifically been designed for human–computer interaction. Therefore, we now introduce the basic circulation features over the EAM before introducing our circulation constraint method.

It is well known that the climate of East Asia is dominated by the East Asian winter monsoon (EAWM) and the East Asian summer monsoon (EASM) in winter and summer, respectively (Christensen and Coauthors, 2014; Wang, 2006). These circulation features define the typical characteristics of air masses and their source regions over the EAM (Dando, 2005). In winter, the EAM is dominated by the westerlies in upper levels, while the winter monsoon prevails at low levels (Seinfeld and Pandis, 2006; Staff Members of the Academia Sinica, 1957). On the other hand, air masses from tropical oceans bring noticeable moisture northward into the EAM (Hsu, 1958). Excluding the local evaporation, there are thus three potential winter moisture sources of the atmosphere over the EAM (i.e., northern continent, tropical ocean, and westerlies). In summer, the westerly winds are considerably weaker and lay substantially farther poleward (Chandrasekar, 2010; McIlveen, 2010). The southwest Asian low triggers the southwest (SW) monsoon and the western North Pacific subtropical high (WNPSH) triggers the southeast (SE) monsoon (Ding, 1994; Zhou et al., 2009). In fact, the monsoonal airflow over the EAM has another source, northern Australia and the adjacent ocean [south (S) monsoon; e.g., Ding (1994); Li et al. (2012c)]. In addition, somewhat humid continental polar summer air masses are transported into the EAM from Siberia (northern continent; e.g., Dando, 2005). Therefore, excluding the local evaporation, there are five potential summer moisture sources of the atmosphere over the EAM (i.e., westerlies, SW monsoon, S monsoon, SE monsoon, and northern continent).

We define moisture source in two different ways. The first is relevant at high spatial resolution (0.5° × 0.5°) and gives qualitative source–sink relationships, omitting the quantitative moisture contribution to the target area (section
Chapter 3. The other gives quantitative moisture contributions from a certain source, although with this definition boundaries are less well defined (section 3.4). Section 3.2 provides a description of the data and methodology used in this study. A summary and conclusions are given in section 3.5.

3.2 Data and methods

3.2.1 Model description

We use the Flexible Particle dispersion model (FLEXPART), a Lagrangian atmospheric transport model, which has been developed and validated by Stohl and James (2004, 2005) to analyze moisture source regions. FLEXPART uses operational data with $1^\circ \times 1^\circ$ resolution from the European Centre for Medium-Range Weather Forecasts (ECMWF) interim reanalysis (ERA-Interim; Dee et al., 2011). The model divides the atmosphere into a large number ($N$) of so-called particles that are assumed to have a constant mass $m = m_a / N$, where $m_a$ is the total atmospheric mass. The model, using three-dimensional wind fields of the ECMWF analyses, then transports each particle backward. Particle positions and values of specific humidity $q$ are calculated and stored.

Because the time resolution is critical for the accuracy of the Lagrangian trajectories (Stohl et al., 1995), we used ECMWF global analyses every 6 h (at 0000, 0600, 1200, and 1800 UTC) and 3-h forecasts at intermediate times (at 0300, 0900, 1500, and 2100 UTC) on 60 model levels to drive the model for a 4-yr (2009–12) period. FLEXPART was started on 31 December 2012, and 80 000 particles were generated every 3 h, randomly from the ground surface to 10 000 m above ground, over the EAM and then moved backward freely with the winds for 10 days. Particle positions and values of $q$ were recorded every 3 h. Although the simulating period is relatively short and may miss low-frequency variations of the climate, it is sufficient to reveal the basic characteristics of moisture flux over the EAM (Sun and Wang, 2014). On the other hand, since Eq.(3.2) (see below) is a statistical relationship and is accurate only for a large number of particles residing over a given area, either $N$ or the area or both must be large (Stohl
3.2. Data and methods

and James, 2004). When simulation accuracy conflicts with the length of simulation period in terms of computational demand, we chose, similar to others, the former (Sun and Wang, 2014; Drumond et al., 2011, 2010; Nieto et al., 2006a; Drumond et al., 2008).

3.2.2 Qualitative source–sink distribution analysis: (E-P) method

Stohl and James (2004, 2005) developed a Lagrangian method to track the moisture in the atmosphere and postprocessing methods to establish its source–sink relationships [evaporation minus precipitation; the \((E - P)\) method hereafter]. This Lagrangian tracking method was widely used during the past decade. Even though the postprocessing method has been modified in several other Lagrangian studies for quantitatively diagnosing moisture source regions (e.g. Sodemann et al., 2008; Gustafsson et al., 2010; Sun and Wang, 2014, 2015), the \((E - P)\) method is appropriate and fundamental for qualitatively detecting the source–sink distributions in relatively high spatial resolution. In addition, it has the advantage in revealing the spatiotemporal evolution of the source–sink distribution (e.g. Chen et al., 2012a). In section 3.3, we detect the source–sink distribution qualitatively using the \((E - P)\) method.

From the output of FLEXPART, \((e - p)\) is diagnosed from a particle’s \(q\) change between two output times \(t\) and is assigned to the particle’s central position during the time step:

\[
e - p = m \frac{dq}{dt} \quad (3.1)
\]

where \(e\) and \(p\) are the rates of moisture increase (by evaporation) and decrease (by precipitation) along the trajectory, respectively.

To diagnose the surface freshwater flux \((e - p)\) in area \(A\), the moisture changes of all particles in the atmospheric column over \(A\) are amassed:

\[
E - P \approx \frac{\sum_{k=1}^{K} (e - p)}{A} \quad (3.2)
\]

where \(K\) is the number of particles residing over \(A\).
Applying Eq.(3.2) along the particle trajectories yields \((E - P)\) values contributed by the particles traveling to the EAM. Therefore, these \((E - P)\) values are conditional \((E - P)\) values and they do not represent the surface net freshwater flux, but only the net freshwater flux into the air mass traveling to the EAM. We refer to these \((E - P)\) values as \((E - P)_c\). The inherent trajectory errors of the model and the quality of the input data are two major limitations of this method to diagnose \((E - P)\) values. However, by using larger regions and longer time periods, trajectory errors can be minimized, as we show here. For more information on this method, the reader is referred to Stohl and James (2004, 2005).

3.2.3 Quantitative source–path attribution analysis: The circulation constraint method

The circulation constraint method proceeds as follows. First, we label each trajectory into one of the predefined categories in section 3.1 based on its initial position (forward in time). Even though the circulation constraint method is robust to the choice of the initialized criteria because of the supervision of the clustering processes, a good initialization requires fewer iterations to create a reasonable clustering, saving noticeable computation time. Inequalities with the latitude and longitude of each particle at the initial time of the trajectory (\(lat_0\) and \(lon_0\); in Table 3.1) are considered as initialized criteria in this research.

Second, we plot the figure for trajectories in each predefined category in the first step. This gives a visual feedback. Normally, the position of each separate trajectory fluctuates considerably and may overlap with trajectories of particles from other sources. This raises a big challenge for trajectory clustering. To solve this problem, additional algorithms (i.e., the constraint algorithms) should be designed to provide supervision to the clustering processes.

Take the particles originating from the northern Indian Ocean as an example. Normally, they belong to the group of tropical ocean in winter and to the southwest monsoon in summer. However, they may also flow westward with the trade winds to the Middle East or North Africa (i.e., northwest of Somalia; Ordóñez et al., 2012), above which region they turn the direction and flow eastward to the EAM with the westerlies. In this case, we group them into the
### Table 3.1: Routines for grouping 10-day backward trajectories into categories, where $lat_0$ and $lon_0$ are the latitude and longitude of each particle at the initial time of the trajectory (forward in time, and the same below); $lat_q$ and $lon_q$ are the latitude and longitude of each particle at the first quarter of the lifetime; $lon_m$ is the longitude at the middle time of the trajectory; and $lat_i$ and $lon_i$ are particle positions at each time step (3h)

<table>
<thead>
<tr>
<th>Priority</th>
<th>Winter</th>
<th>Season</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Northern continent</td>
<td>$60^\circ &lt; lon_0 &lt; 140^\circ$&lt;br&gt;$lat_0 &lt; 50^\circ$&lt;br&gt;$lon_m &gt; 60^\circ$&lt;br&gt;or&lt;br&gt;$80^\circ &lt; lon_i &lt; 140^\circ$&lt;br&gt;$lat_i &lt; 60^\circ$&lt;br&gt;$lon_{i-1} &gt; 60^\circ$</td>
<td>Westerlies</td>
<td>$lon_0 &lt; 40^\circ$&lt;br&gt;$lon_m &lt; 130^\circ$&lt;br&gt;or&lt;br&gt;$lon_0 &lt; 40^\circ$&lt;br&gt;$lon_m &lt; 130^\circ$</td>
</tr>
<tr>
<td>2 Tropical ocean</td>
<td>$lon_0 &gt; 55^\circ$&lt;br&gt;$lat_0 &lt; 15^\circ$&lt;br&gt;or&lt;br&gt;$lon_0 &gt; 130^\circ$&lt;br&gt;$lat_0 &lt; 30^\circ$&lt;br&gt;$lon_m &gt; 50^\circ$</td>
<td>SE monsoon</td>
<td>$lon_0 &lt; -140^\circ$&lt;br&gt;$lon_q &gt; 140^\circ$&lt;br&gt;or&lt;br&gt;$lon_0 &gt; 150^\circ$&lt;br&gt;$lon_q &gt; 140^\circ$&lt;br&gt;$lon_0 &gt; 90^\circ$&lt;br&gt;$lat_0 &gt; 40^\circ$</td>
</tr>
<tr>
<td>3 Westerlies</td>
<td>$lon_0 &lt; 60^\circ$&lt;br&gt;$lon_m &lt; 60^\circ$&lt;br&gt;or&lt;br&gt;$lon_0 &lt; 80^\circ$&lt;br&gt;$lon_0 &gt; 15^\circ$</td>
<td>Northeast Asia</td>
<td>$lon_0 &gt; 120^\circ$&lt;br&gt;$lat_i &lt; 30^\circ$&lt;br&gt;$lat_{i-1} &gt; 30^\circ$</td>
</tr>
<tr>
<td>4 Local Other particles Northern continent</td>
<td>$lon_0 &gt; 90^\circ$&lt;br&gt;$lat_0 &gt; 40^\circ$&lt;br&gt;$40^\circ &lt; lon_0 &lt; 100^\circ$&lt;br&gt;$lon_0 &lt; 40^\circ$&lt;br&gt;$40^\circ &lt; lon_0 &lt; 100^\circ$</td>
<td></td>
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<tr>
<td>5 Westerlies</td>
<td>$lat_0 &lt; 20^\circ$&lt;br&gt;$lon_q &lt; 40^\circ$&lt;br&gt;$40^\circ &lt; lon_0 &lt; 100^\circ$&lt;br&gt;$lon_0 &lt; 40^\circ$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 SW monsoon</td>
<td>$lat_0 &lt; 20^\circ$&lt;br&gt;$lon_q &gt; 40^\circ$&lt;br&gt;$40^\circ &lt; lon_0 &lt; 100^\circ$&lt;br&gt;$lon_0 &lt; 40^\circ$</td>
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<tr>
<td>7 S monsoon</td>
<td>$100^\circ &lt; lon_0 &lt; 130^\circ$&lt;br&gt;$lat_0 &lt; 20^\circ$&lt;br&gt;$lon_m &lt; 80^\circ$&lt;br&gt;$lat_q &gt; 15^\circ$</td>
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<tr>
<td>8 Westerlies</td>
<td>$lon_m &lt; 80^\circ$&lt;br&gt;$lat_q &gt; 15^\circ$</td>
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<tr>
<td>9 Local Other particles</td>
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cluster of westerlies rather than the tropical ocean or the southwest monsoon. Knowledge on general circulation features over the EAM tells us that the main difference is whether particles have flowed westward noticeably or not. Thus, we can use extra algorithms to force them into the cluster of westerlies. In this study, we use the longitude of the particle at the first quarter of their lifetime ($lon_{q}$) as the criterion to separate them in the summer case (see priorities 5 and 6 in Table 3.1 for summer).

One may have noticed that the westerlies appeared three times in the routines shown in Table 3.1. With hard clustering, particles are forced in one and only one group. Since each separate trajectory fluctuates considerably and may overlap with trajectories of particles from other sources, particles may fulfill more than one group membership criteria in Table 3.1. By giving order to different group membership criteria, we gave them different priorities to classify the overlapped particles and forced each particle into only one group.

Third, we repeat the visual inspection in the second step and modify the criteria for both the initial position (forward in time) and the constraint algorithms.

Fourth, when the percentage of trajectories, which have been grouped into the reasonable clusters, is larger than a user-defined threshold, the iteration may be allowed to terminate. In the present study the threshold is 99% and the algorithms in Table 3.1 are the final clustering algorithms we derived.

Fifth, we calculate the cluster mean trajectory (called path hereafter) for each group. We then get several paths, where each path corresponds to a certain source. Note that the ending area of the path is not necessarily the moisture source; the whole area that the path passes over can be the moisture source.

In the sixth step, we record the number of particles from each source and the specific humidity at the moment when they flow into the EAM. Since the mass of each particle is given in the FLEXPART simulation, we can calculate the amount of moisture from each source via a certain path into the target area.

Finally, the fate of moisture (i.e., precipitated or stay in the atmosphere) is
3.3. Qualitative source–sink distribution analysis

The precipitation efficiency of air masses transported through each pathway is defined as

\[ P_e = \frac{Q_0 - Q}{Q_0} \]  

(3.3)

where \( Q \) and \( Q_0 \) are the amount of moisture contained in air parcels transported through a certain path at the end of trajectories (forward in time) and at the time when the air parcels are transported into the EAM, respectively. Therefore, positive \( p_e \) indicates that the specific humidity of air decreased after entering the EAM, and thus the air mass brought effective moisture that can contribute to forming net precipitation in the EAM. In contrast, negative \( p_e \) indicates that the air would become moister by absorbing moisture instead of forming net precipitation. For example, for an air parcel losing half of its moisture by precipitation, the precipitation efficiency is 50%; for an air parcel gaining moisture as much as its original content, the precipitation efficiency is -100%.

3.3 Qualitative source–sink distribution analysis

The air masses residing over the EAM were tracked backward for a period of 10 days by FLEXPART. To assess where the particles gain or lose moisture, the conditional freshwater flux [i.e., \( (E - P)_c \)] was calculated on a 0.5° × 0.5° grid and averaged over seasonal periods and the full 4-yr period. Similar to Stohl and James (2005), the nomenclature \( (E - P)_c^n \) was used to show \( (E - P)_c \) on a certain day, and \( (E - P)_c^{n,1} \) used to show \( (E - P)_c \) integrated from day 1 to day \( n \), where \( n \) is a negative number indicating backward tracking. In the figures, blue colors indicate regions where \( (E - P) < 0 \), which means precipitation dominates over evaporation and the air masses lose moisture. Regions with blue colors are therefore moisture sinks. In contrast, red colors indicate regions where \( (E - P) > 0 \), which means evaporation dominates over precipitation and air masses gain moisture. Regions with red colors are therefore moisture sources.
Figure 3.1: Annually averaged fields for the EAM from the 4-yr particle backward tracking: (a) \((E - P)c^{-2}\), (b) \((E - P)c^{-4}\), (c) \((E - P)c^{-8}\), and (d) \((E - P)c^{-10.1}\), which is, averaged over 10 days back. The box illustrates the domain of the EAM in this study. The four maps are plotted with the same scope in order to illustrate the spatiotemporal evolution of the source–sink distributions.

3.3.1 Annual mean source–sink relationship to the EAM

Figures 3.1a–c show the spatiotemporal evolution of the source–sink distribution by the averaged \((E - P)c\) fields. On the –8th day (Figure 3.1c), which means the eighth day backward in time, the particles spread over a vast area, including most parts of the North Atlantic and Eurasia. Four days later (Figure 3.1b), particles are closer to the EAM while a small part of them can still be found over the North Atlantic. The northern Indian Ocean has generally been converted from moisture source to sink. Comparison of Figure 3.2b to Figure 3.3b reveals the reason for this source–sink conversion. It can be seen that in summer (Figure 3.3b) particles are mainly located north of the equator, while in winter (Figure 3.2b) moisture sinks can be found over the northern Indian Ocean near the equator (see more details in the next subsection). Thus, the moisture sinks over this region in Figure 3.1b are mainly controlled by the source–sink relationship in winter. On the other hand, though a large amount of particles are transported from the Atlantic via Eurasia to the EAM, they generally keep on
losing moisture, especially 2 days prior to the EAM (Figure 3.1a). In this sense, it remains an open question whether the estimate of van der Ent et al. (2010), who suggest that moisture from the Eurasian continent is responsible for 80% of China’s water resources, is valid. In particular, it is crucial to diagnose whether it is plausible, and if the amount is correct, that the net precipitation relating to the westerlies can be formed, especially with regard to water resources. We will come back to this issue in section 3.4.

The annual mean values of $(E - P)_c^{-10,1}$ depict the synoptic moisture source–sink relationships to the EAM (Figure 3.1d). The dominant feature is that the northern Indian Ocean, the East and South China Seas, and most parts of China are diagnosed as noticeable moisture source regions. Intuitively, it may be explained by the well-known summer monsoon (e.g. Ding, 1994) and the importance of local moisture recycling (Dirmeyer et al., 2009). However, more details still need to be clarified, such as how the moisture is transported from the source regions into the EAM and to what extent do these source regions affect the water resources of the EAM? These questions will be discussed in section 3.4.

### 3.3.2 Seasonal mean source–sink evolution

Because of distinguishable and well-known variations of the general circulation between summer and winter, seasonally climatologic patterns are not always visible in the annual means. On the other hand, in order to serve future studies on the floods and droughts over China where floods mainly occur in summer and the prolonged droughts normally start in winter (Yao, 1942; Ding, 1994; Sun and Yang, 2012), we now direct our attention to the source–sink features in winter and summer over the EAM, respectively.

Figure 3.2 shows averaged values of $(E - P)_c$ for winter [December–February (DJF)]. The $(E - P)_c$ fields on different days reveal the spatiotemporal evolution of the source–sink distributions. On the –8th day, the particles spread over a vast area (Figure 3.2c). Regions between $10^\circ$ and $40^\circ$N in Eurasia, Africa, and part of the western North Pacific are mainly identified as moisture sources, and other regions mainly act as moisture sinks. For arid regions such as North Africa and the Middle East, according to Stohl and James (2005), dry particles can gain
Chapter 3.

FIGURE 3.2: As in Figure 3.1, but for winter (DJF). The black ellipse in (a) indicates the location of the Pamir and the Hindu Kush mountain ranges.

moisture by mixing with other air masses instead of absorbing moisture from the local evaporation. In this sense, the diagnosed source regions at the beginning of the trajectories (forward in time) should be interpreted with more caution, and it also highlights the importance of the $(E - P)^{10,1}$ values (Figure 3.2d). Meanwhile, it can be seen that on the 4th day (Figure 3.2b), when humid particles originally located over the Atlantic flow to North Africa and the Middle East, they lose moisture due predominately to the mixing with other dry particles. On the 2nd day, the extent of moisture source regions has been further decreased (Figure 3.2a). Only the EAM and the adjacent regions are identified as moisture sources. It is noticeable that large precipitation occurs over western China, where air masses are forced up by the mountain chains (particularly the Himalayas, the Pamir Mountains, and the Hindu Kush). This agrees with the previous work of Rohli and Vega (2012). In addition, the northern Indian Ocean, especially the Bay of Bengal, is a strong moisture sink because of the moist air from the tropic ocean (see below).

The source–sink distribution patterns over the oceanic regions, including the northern Indian Ocean and the western Pacific, are mainly subject to the general circulation patterns (Seinfeld and Pandis, 2006). This feature is more prominent
3.3. Qualitative source–sink distribution analysis

at the beginning of the trajectories (Figure 3.2c). For oceanic regions near the equator, the rising warm, moist air particles lose moisture and are thus diagnosed as moisture sinks. Going farther north, the oceanic regions are diagnosed as moisture sources because, on average, air particles descend and gain moisture from sea surface evaporation. During the following days (Figures 3.2a, b), particles from the tropical oceans flow westward, curve northward and northeastward, and then penetrate southern China (see more details in section 3.4). On average, particles lose moisture during the northward flow processes, as evidenced by Figures 3.2a and 3.2b and later by Figure 3.4. It is worth noting that, based on our circulation constraint method, we found that the strong moisture sources over the oceanic regions close to China are mainly related to the advection of particles from the local region and the northern continent. When relatively dry particles flow over the oceans, they generally gain large amounts of moisture and become more humid (Figures 3.2a, b).

The averaged value over all 10-day backward transport for winter (Figure 3.2d) shows the synoptic moisture source–sink relationship to the EAM in winter. The dominant features seen on the map are the positive values of \((E - P)_c^{10,1}\) over the East China Sea, South China Sea, and the western North Pacific, indicating these regions are moisture sources of the EAM in winter. The values of \((E - P)_c^{10,1}\) over central, eastern, southeastern, and northern China are positive, indicating the self-feeding of atmospheric moisture from local evaporation in winter, as suggested by Dirmeyer et al. (2009). Eurasia and North Africa are moisture sinks.

Figures 3.3a–c show the spatiotemporal evolution of the source–sink distributions for summer [June–August (JJA)]. It can be seen that the source–sink patterns are stable, especially when compared with the patterns in winter. It is noticeable that the \((E - P)_c\) fields are strongly controlled by the summer monsoon. On the –8th day (Figure 3.3c), the northern Indian Ocean is the most prominent moisture source for the EAM because of the powerful southwest monsoon (Ding, 1994). Similar results are also observed in previous studies even though their target regions are smaller (e.g. Sun and Wang, 2015; Wei et al., 2012; Drummond et al., 2011). For the source–sink patterns over the western Pacific, these
Figure 3.3: As in Figure 3.1, but for summer (JJA).

are mainly controlled by the southeast monsoon. Moisture sources can be diagnosed for regions around (20°N, 160°E). This feature is governed by the WNPSH, for the relatively dry particles descend and gain moisture from the sea surface evaporation. Moisture sinks could be seen on the outskirts of the WNPSH region, which means that, on average, the air current driven by the southeast monsoon loses moisture before penetrating the EAM. This feature becomes more pronounced in the following days (Figure 3.3a, b). A similar feature could be found for the southwest monsoon, which loses moisture over the Indochina peninsula, because the air masses arriving from the northern Indian Ocean are moist and orographically lifted. Considering this similarity, it would be interesting to compare the relative importance of the two branches of summer monsoon to the precipitation over the EAM. This will be done in section 3.4.

The averaged value over all 10-day backward transport for summer (Figure 3.3d) shows the synoptic moisture source–sink distribution for the EAM in summer. Because the source–sink patterns are stable in summer, the $(E - P)_c^{-10,1}$ fields are similar to the $(E - P)_c$ fields on the −8th day. Positive $(E - P)_c^{-10,1}$ values over the northern Indian Ocean, the western part of the South China Sea, and regions controlled by the WNPSH indicate the importance of summer monsoon to the moisture supply for the EAM. Positive $(E - P)_c^{-10,1}$ values over central,
eastern, and northern China indicate the self-feeding of atmospheric moisture from local evaporation, which has already been suggested by Dirmeyer et al. (2009); Sun and Wang (2015), and Drumond et al. (2011). Similar to winter, Eurasia is also diagnosed as a moisture sink in summer.

3.4 Quantitative source–path attribution analysis

Using the circulation constraint method of section 3.2, the main sources and transport paths of the moisture over the EAM can now be depicted clearly. The relative importance of each source for supplying moisture into the EAM (e.g. Ding, 1994, Fig.3.1.15) has now been quantified. The fates of moisture from different sources have further been diagnosed. Thus, the importance of different moisture sources can be evaluated more objectively.

3.4.1 Source–path attribution in winter

For particles over the EAM in winter, we designed routines (Table 3.1) for grouping the 10-day backward trajectories into four categories: northern continent, tropical ocean, westerlies, and local, which correspond to particles transported by the winter monsoon, from the tropical ocean, by the westerlies, and particles not belonging to any of them. The particle attributes for each group were calculated (Table 3.2) and the cluster mean trajectories plotted in Figure 3.4. Even though the paths look smooth, one needs to keep in mind that each separate trajectory may fluctuate considerably.

It can be seen from Figure 3.4 that most of the air masses over the EAM are transported from the west by westerly winds (73.5%). The air masses mainly come from Eurasia, some even from the western Pacific, via the Pacific Ocean, North America, the Atlantic Ocean, North Africa, and Eurasia to the EAM. The air masses are somewhat humid over the Atlantic and then lose moisture when passing through North Africa and the Middle East. Comparing Figure 3.4 with Figure 3.2c reveals that the moisture lost over Europe is more than the moisture gained over North Africa during the initial 3-day trajectories (forward in time). The mean specific humidity is around 0.9 g kg$^{-1}$ when the westerly winds pass
Figure 3.4: The 4-yr cluster mean trajectories in winter. Light gray lines represent 8000 particles randomly chosen from particles released in winter of 2009; colored lines are the cluster mean trajectories of all the particles released in winter during the 4-yr period. The color indicates the mean specific humidity (g kg\(^{-1}\)) of the air parcel in each path, the line width indicates the number of particles belonging to each cluster, the black ellipse indicates the location of the Ural Mountains, and the black arrow indicates the direction of the mean local moisture flow. For other branches of moisture flow (from north to south: northern continent, westerlies, and tropical ocean), the mean direction is to the EAM and the arrows are omitted.

through the Middle East and come into the EAM. Though the westerly winds are the driest moisture sources, they still provide 49% of the moisture over the EAM in winter (Table 3.2).

The air masses from the northern continent are dry, especially when passing over the Ural Mountains and flow into Siberia (Figure 3.4). After that, they keep on absorbing moisture from local evaporation and become more and more humid. Therefore, when flowing into the EAM, they are more humid than the westerlies, providing 12% of the moisture over the EAM in winter. However, similar to the westerlies, they do not form net precipitation over the EAM and tend to absorb even more moisture according to the negative value of the mean precipitation efficiency shown in Table 3.2.

The maritime tropical air masses are moist (specific humidity more than 4
3.4. Quantitative source–path attribution analysis

TABLE 3.2: Particle attributes for each identified source in winter (DJF).

<table>
<thead>
<tr>
<th>Source</th>
<th>Particle number (%)</th>
<th>Moisture amount (%)</th>
<th>Mean specific humidity (g kg(^{-1}))</th>
<th>Precipitation efficiency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Westerlies</td>
<td>73.49</td>
<td>49.01</td>
<td>0.888</td>
<td>-17.55</td>
</tr>
<tr>
<td>Tropical ocean</td>
<td>9.74</td>
<td>16.03</td>
<td>2.192</td>
<td>9.94</td>
</tr>
<tr>
<td>Northern continent</td>
<td>9.31</td>
<td>11.90</td>
<td>1.702</td>
<td>-57.3</td>
</tr>
<tr>
<td>Local</td>
<td>7.46</td>
<td>23.06</td>
<td>4.117</td>
<td>-4.15</td>
</tr>
</tbody>
</table>

g kg\(^{-1}\). They lose moisture on their way to the EAM, and the mean specific humidity is approximately 2.2 g kg\(^{-1}\) when they flow into the EAM. The tropical ocean is the most humid moisture source and the only source region from which moisture forms net precipitation over the EAM (Table 3.2). It is worth noting that, on average, the moisture from tropical ocean mainly influences the southern part of the EAM and cannot penetrate northward because of the intensity of the Siberian high (Dando, 2005).

Approximately 7.5% of the particles do not belong to any of the above three source regions, which means the positions of those particles are adjacent to or over the EAM at the start of the trajectories (forward in time). Therefore, particles in this group tend to stay over the EAM and the adjacent regions during the 10-day lifetime, and the moisture contained by them is referred to as local moisture. It can be seen from Figure 3.4 that they are humid at the beginning and become even more humid in the following days. This can be explained by the strong local evaporation derived from Figure 3.2. However, according to the mean precipitation efficiency shown in Table 3.2, these humid local air masses do not provide net precipitation over the EAM. Thus, they tend to stay over the EAM or flow to other regions.

3.4.2 Source–path attribution in summer

Similar to winter, we designed routines for grouping the 10-day backward trajectories in summer into seven categories: westerlies, SW monsoon, S monsoon, SE monsoon, northeast Asia, northern continent, and local (Table 3.1). The particle attributes for each group have been calculated (Table 3.3) and the cluster
mean trajectories were plotted (Figure 3.5). According to our trajectory simulation, we found a small branch of particles, which come from the northeast Asian continent, then flow via Japan and the East China Sea to southern China. These air masses are dry at the beginning (forward in time). Even though they absorb moisture when passing over the oceanic region, the mean specific humidity is only 4.4 g kg\(^{-1}\) when they flow into the EAM. Consequently, they bring only 0.5% of the moisture into the EAM. To our knowledge, despite Zhou and Yu (2005), the existence of this branch of air masses has rarely been mentioned, and they may have unknown importance to the precipitation formation in China. Therefore, we grouped these air masses into a separate category, named northeast Asia, even though they provide the least moisture to the EAM.

![Figure 3.5](image.png)

**Figure 3.5:** As in Figure 3.4, but for summer. Light gray lines are 8000 particles randomly chosen from particles released in summer of 2009. The black arrow indicates the direction of the mean local moisture flow. For other branches of moisture flow (counterclockwise: SW monsoon, S monsoon, SE monsoon, northeast Asia, northern continent, and westerlies), the mean direction is to the EAM and the arrows are omitted.

It can be seen from Table 3.3 that, though much less than in winter, the westerly winds transport the largest branch of the air masses into the EAM (39%) in summer. However, these air masses are dry and only provide 18% of the moisture into the EAM in summer. In addition, since the precipitation efficiency is
3.4. Quantitative source–path attribution analysis

<table>
<thead>
<tr>
<th>Source</th>
<th>Particle number (%)</th>
<th>Moisture amount (%)</th>
<th>Mean specific humidity (g kg(^{-1}))</th>
<th>Precipitation efficiency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Westerlies</td>
<td>38.78</td>
<td>17.95</td>
<td>2.45</td>
<td>-24.52</td>
</tr>
<tr>
<td>SW monsoon</td>
<td>21.90</td>
<td>40.43</td>
<td>9.77</td>
<td>19.36</td>
</tr>
<tr>
<td>SE monsoon</td>
<td>12.15</td>
<td>14.83</td>
<td>6.46</td>
<td>-4.78</td>
</tr>
<tr>
<td>S monsoon</td>
<td>7.99</td>
<td>11.41</td>
<td>7.56</td>
<td>9.84</td>
</tr>
<tr>
<td>Northern continent</td>
<td>5.36</td>
<td>4.92</td>
<td>4.86</td>
<td>-43.3</td>
</tr>
<tr>
<td>Northeast Asia</td>
<td>0.65</td>
<td>0.54</td>
<td>4.4</td>
<td>-27.77</td>
</tr>
<tr>
<td>Local</td>
<td>13.17</td>
<td>9.9</td>
<td>3.98</td>
<td>-16.86</td>
</tr>
</tbody>
</table>

negative, the importance of westerlies to the water resources in the EAM should not be overestimated.

The southwest monsoon is the second-largest airmass source and the largest moisture source of the EAM in summer. From Figure 3.5, it can be seen that, on average, the air masses are humid (specific humidity is approximately 6–10 g kg\(^{-1}\)) before entering the Bay of Bengal. After that, the air masses absorb more moisture and become very moist (specific humidity is larger than 10 g kg\(^{-1}\)). After making landfall, they mainly lose moisture over the Indochina peninsula (this can also be noticed in Figure 3.3). The mean specific humidity is 9.8 g kg\(^{-1}\) when they flow into the EAM, providing more than 40% of the moisture to the EAM and making southwest monsoon the most humid and abundant moisture source of the EAM (Table 3.3).

The southeast monsoon is both the second-largest monsoonal airflow toward the EAM and the second-largest monsoonal moisture source of the EAM, providing 12% of the air masses and 15% of the moisture, respectively. According to our trajectory simulation, the mean position of the southeast monsoon moves northward continuously from June to August (not shown), corresponding to the movement of the WNPSH. Because of the well-known relations between the WNPSH and the precipitation features over the EAM (Ding, 1994), it is worth diagnosing the relations between the southeast monsoon and the summer precipitation in the EAM in future research. According to our simulation, however,
the precipitation efficiency of the southeast monsoon is 25%, not as high as it was expected.

The south monsoon provides the least monsoonal moisture with the smallest monsoonal airflow into the EAM, 11% and 8%, respectively. However, the south monsoon and the southwest monsoon are the only two moisture sources that provide net precipitation into the EAM in summer. The northern continent is the second least in both the air mass and the moisture inflow in summer, providing 5% of the moisture with 5% of the inflow air masses. Different than with the circulation feature in winter, the local air masses are relatively more important, providing 10% of the moisture with 13% of the inflow air masses to the EAM (Table 3.3).

3.5 Summary and conclusions

A Lagrangian method has been successfully implemented to detect the moisture source–sink relationships to the EAM. The annual and seasonal mean conditions for a 4-yr period (2009–12) were studied. The analysis suggested that the northern Indian Ocean and regions governed by the WNPSH are the main moisture source regions in summer, highlighting the importance of the summer monsoon. Similar results were obtained both in traditional moisture source studies (e.g. Ding, 1994; Staff Members of the Academia Sinica, 1957; Hsu, 1958) and in recent trajectory studies (e.g. Sun and Wang, 2015; Wei et al., 2012; Drumond et al., 2011). The East China Sea, South China Sea, and the western North Pacific are the main moisture source regions in winter. These results are in good quantitative agreement with previous trajectory studies (Sun and Wang, 2014, 2015) even though their target regions are smaller. Local evaporation over the central, eastern, and northern parts of China plays an important role as moisture sources during the whole year, consistent with the quasi-isentropic backtrajectory study by (Dirmeyer et al., 2009).

Though the \((E - P)\) method is sophisticated and powerful, the diagnosed source–sink relationships should be interpreted with more caution. In section 3.3, the source–sink relationships at the beginning, middle, and end stages of
the backward simulations have been investigated, and the overall relationships have been depicted by the $(E - P)_c^{10.1}$ values. In this way, we provided detailed maps of the source–sink relationships to the EAM and the spatiotemporal evolution of the source–sink distribution. Major source–sink distribution patterns have further been interpreted either based on the relevant circulation features (e.g. Seinfeld and Pandis, 2006) or on the traditional understandings of the moisture sources of China (e.g. Ding, 1994; Staff Members of the Academia Sinica, 1957; Hsu, 1958). In particular, the feedbacks of our circulation constraint method shown in section 3.4 give us a chance to interpret these patterns in a rational and insightful way (e.g., why the oceanic regions close to China are diagnosed as strong moisture sources).

Several studies have investigated the atmospheric moisture transport over China. While to some extent they identified moisture sources over China (Simmonds et al., 1999; Zhou and Yu, 2005), or over certain regions of China (Li et al., 2012b), they were not able to calculate these with high temporal or spatial precision because they did not use real trajectories of atmospheric particles. Unfortunately, we were not able to calculate the sources and sinks for a longer period because of computational and data handling constraints as a result of our choice for high accuracy, rather than temporal coverage. The results are thus strictly only valid for the period 2009–12. This period has seen a moderately strong monsoon index (e.g., http://bcc.cma.gov.cn/EAMAC/) and was roughly equally impacted by the ENSO cycle (e.g., www.bom.gov.au/watl/enso/). We therefore consider the results fairly typical for these conditions.

We presented a circulation constraint method to detect where the moisture over the EAM comes from and how it travels there. The quantitative importance of different source regions and the fate of moisture from each source region could thus be calculated for the first time in a more objective manner. We found that in winter, the largest inflow is through the dry westerlies; however, these do not form net precipitation. Winter precipitation is driven by the much smaller contribution of the tropical oceans. In summer, the summer monsoons are the most
important moisture sources, providing 67% of the moisture with 42% of the inflow air masses. In general, maritime air masses contain more moisture than continental air masses and are more prone to form net precipitation over the EAM. However, according to this research, higher specific humidity does not necessarily mean higher precipitation efficiency. More detailed analysis on the particle trajectories combined with topography and local meteorological processes in future research can give explanations on why moisture transported from different pathways has different probability to form precipitation.

The advantage of our method is that it adds constraints from the general circulation features. Since the position of the seasonal cluster mean paths of air masses from the source regions to the EAM are relatively stable, the definition of the moisture source region based on circulation feature is thus also stable. In addition, while the former approaches only depict the limits of the uptake sectors (Sodemann et al., 2008; Sun and Wang, 2014, 2015), our circulation constraint method further gives the major flow paths and the variation of the moisture content on the paths.

Our present study aimed for a better understanding of the main moisture source regions over the EAM and provided a general description about the percentage and processes of moisture transported into the EAM. Though it captured the major attributes of the air masses from different source regions, there were two details that merit specific attention. First, in section 3.3, the oceanic regions close to China are diagnosed as strong moisture sources to the EAM in winter. However, this feature was not apparent in section 3.4. In fact, the air masses from each source could be further divided into two categories: one that flows into the EAM directly and one that has flowed to the adjacent oceans and then curves back into the EAM. Thus, the latter one becomes more humid and makes the adjacent oceans the strong moisture source regions of the EAM. Second, the circulation patterns and the moisture content are different between upper and lower levels. Thus, the moisture source–sink relationships can also be different with air mass in different levels. In Chapter 2, we investigated these vertical features in a case study and similar study can be carried out from the climate perspective in the future.