Multiple Flow Regimes in the Northern Hemisphere Winter. 
Part II: Sectorial Regimes and Preferred Transitions

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ABSTRACT

This paper presents an observational analysis of recurrent flow patterns in the Northern Hemisphere (NH) winter, based on a 37-year series of daily 700-mb height anomalies. Large-scale anomaly patterns that appear repeatedly and persist beyond synoptic time scales are identified by searching for local maxima of probability density in a phase subspace, which is spanned by the leading empirical orthogonal functions (EOFs).

By using an angular probability density function (PDF), we focus on the shape, not magnitude, of the anomaly patterns. The PDF estimate is nonparametric; that is, our algorithm makes no a priori assumption on symmetry with respect to the climatological mean as in one-point correlation and rotated EOF analyses. The local density maxima are searched by iterative bump hunting.

Based on observed partial decoupling between the Pacific (PAC) and the Atlantic–Eurasian (ATL) sectors, the classification algorithm is applied separately to each of the two. Seven PAC and six ATL patterns are obtained. Anomaly maps that belong to the neighborhood of each PDF peak are associated with distinct flow regimes. These include regional blocked and zonal flows, and wave train–like anomaly patterns, some of them well known from previous studies, others revealed by our analysis for the first time.

Successive appearances of flow regimes are generally separated by unclassifiable, transient periods. A Markov chain describes transitions between different flow regimes, highly likely, as well as unlikely routes of transition exist. Chains of preferred transitions may be related to the existence of oscillatory modes in the NH extratropics.

A synoptic characterization of onsets and breaks for the flow regimes obtained is given by composing, in situ evolutions of anomaly patterns, slow westward shifts of high-latitude anomaly centers, and successive downstream increase of anomaly magnitudes are the typical signatures of such events.

1. Introduction

Variations in wintertime extratropical atmospheric flows are characterized by the sporadic appearance of persistent patterns out of the general chaotic background (e.g., Dole and Gordon 1983; Horel 1985; Kimoto and Ghil 1993, hereafter referred to as Part I). The fact that most of these persistent patterns looked familiar to experienced long-range forecasters lead to the idea of Grosswetterlagen (Bauer 1951). Although it has long been a common operational practice to think of evolution and changes in large-scale circulations in terms of such Grosswetterlagen—for example, blocked and zonal flows (Namias 1953, 1982)—few systematic efforts have been made until recently to substantiate this idea on an objective and reproducible basis. In this study, we reexamine identification of typical persistent and recurrent large-scale flow patterns and their temporal evolution with the aid of a long upper-air dataset and a practical computational algorithm based on a conceptual framework suggested by nonlinear dynamics.

In Part I, it was shown that the identification of Grosswetterlagen can be approached by examining multivariate probability density distributions in the phase space of large-scale atmospheric flows. While conceptually straightforward, such an ambitious approach generally suffers from an inherent difficulty arising from the limitation in available sample size. Despite this, it was demonstrated in Part I and related studies (Buzzi et al. 1986; Mo and Ghil 1987, 1988; Molteni et al. 1990) that evidence exists for the inhomogeneous nature of the sample density distributions. In Part I, this was illustrated by the use of bivariate probability density functions (PDFs) of the time co-

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efficients (or principal components: PCs) of the leading Northern Hemisphere (NH) empirical orthogonal functions (EOFs).

In this paper (Part II of the study), a classification of large-scale anomaly patterns in two sectors of the NH, that is, PAC (from 120°E eastward to 60°W) and ATL (from 60°W eastward to 120°E), is presented. Such a sectorial analysis has been suggested by Part I. Furthermore, the smaller the number of spatial degrees of freedom, the more confidence can be expected. The classification algorithm is based on multivariate PDFs as in Part I, but is tailored to the meteorological problem at hand by retaining only information on patterns of the anomaly maps, and not on their magnitudes. This will focus the study on the angular inhomogeneities found in Part I, in which it is argued that inherent multimodality in higher, and more physically plausible, dimensions can be obscured in low-dimensional explorations due to the existence of a great number of sample maps projecting near the origin (that is, the climatological mean). Local maxima in PDFs are sought by a simple algorithm called bump hunting. Many synoptically familiar patterns are identified. In addition to patterns well known from teleconnection analysis (e.g., Wallace and Gutzler 1981, WG hereafter; Ebens 1984) and rotated EOF analysis (Barstow and Livezey 1987), that is, the Pacific/North American (PNA) pattern, North Atlantic Oscillation (NAO), and Eurasian (EU) wave trains, typical Ω-shaped blocking patterns are found in both the Pacific and the Atlantic. Interrelations between the two sectors are addressed in addition to the relation with the hemispheric analysis of Part I.

Low-frequency variability (LFV) is examined by using a Markov-chain description and a compositing technique. The former was proposed by Ohl (1987) and used by Mo and Ghil (1987, hereafter MG1; 1988, hereafter MG2) to study transitions between persistent and recurrent anomalies; the latter is similar to Dole's (1986b; 1989) and is used to study synoptic evolutions around onsets and breaks of each regime.

In section 2 we describe the data. In section 3, statistical methods used are discussed. The classification results are presented in section 4. Transitions between various flow regimes are described in section 5, while section 6 presents selected results of the composite analysis. A summary and concluding remarks follow in section 7.

2. Data

The dataset used in this study is the same as in Part I. It consists of daily values of the NH 700-mb heights given on an approximately uniform area grid of 358 points (Barstow and Livezey 1987; BL hereafter). Thirty-seven northern winters, from December 1949 to February 1986, are studied. The winter here is defined as a 90-day period starting on 1 December, and a few days at the end of November and beginning of March are used for the averaging and filtering. The seasonal cycle, averaged over 37 years, is removed from the daily gridpoint heights to define the height anomalies; no attempt has been made to remove interannual signals. A 10-day low-pass filter (Blackmon 1976) is applied to the anomalies when temporal smoothness is desired. These are referred to as low-pass (filtered) anomalies. Anomalies without the 10-day filtering are called unfiltered. The total 700-mb heights, that is, the average seasonal cycle plus unfiltered anomalies, are referred to as unprocessed heights.

As discussed in Part I, the 3330 (= 90 × 37) maps are not statistically independent. The number of independent realizations, or effective sample size, is estimated to be somewhere between 300 and 700.

3. Statistical methodology

As discussed in Part I, the identification of recurrent and persistent flow patterns is conceptually best approached by searching for local maxima of probability density in the atmosphere's phase space. Although visual inspection, as adopted in Part I, is a straightforward and illuminating way to identify interesting inhomogeneities in PDFs, it becomes extremely difficult in three or more dimensions. Furthermore, examining PDFs evaluated using various data subsets may be needed in order to put regions of relative density maxima into focus. They do not always appear (cf. Part I) as distinct, isolated maxima in PDFs. An objective and unambiguous algorithm is desired, therefore, to overcome this difficulty.

In our classification algorithm, first the gridded anomaly maps are projected onto a few leading EOFs (section 3a of Part I); the EOFs used here are defined in two complementary sectors of the NH, PAC, and ATL, with the 120°E and 60°W meridians as boundaries. Then, we evaluate multivariate angular PDFs, to be discussed below, in a subspace defined by the leading EOFs of each sector and search for its maxima by an algorithm called bump hunting. Examination of sectorial flow patterns benefits from the fact that the number of temporal degrees of freedom relative to the spatial ones becomes greater than in a hemispheric analysis. The division of the NH is based on several considerations.

First, the boundaries approximately separate two major centers of low-frequency variance over the North Pacific and over the North Atlantic ~ Eurasia (cf. Blackmon et al. 1984a). Second, Kimoto (1987) showed that it is possible to form two groups of varimax-rotated NH EOFs (cf. Horel 1981), whose major features are concentrated in either one of the sectors; lag-zero temporal decorrelation among the varimax-rotated EOF modes, resulting from the analysis procedure, guarantees approximate independence.
between the two sectors. On the other hand, the centers of action of pairs of EOFs localized in the same sector still show substantial overlaps. Third, in their classification of NH anomaly patterns, MG2 noted that most of them are "local," that is, sectorially confined (their Fig. 10). Finally, Part I of this study shows that NH flow regimes, as identified by bivariate PDFs, can be thought of as pairs of zonal and blocked flows in each of the two sectors (Figs. 11a and 14 of Part I).

a. Angular PDFs

The usual Euclidean PDF based on all sample maps, as shown in Fig. 10 of Part I, tends to show interesting inhomogeneities as elongated ridges of equi-PDF surfaces in hyperspace (Kimoto 1987 examined PDFs up to five dimensions). This means that we may not be able to discuss precise radial locations of the maxima, especially with a limited sample size, for Euclidean PDFs. But distinction is possible by considering angular distance in phase space. The cosine of the angle viewed from the origin, that is, from the climatological mean, corresponds to pattern correlation $p$ as defined by Eq. (7) of Part I. The pattern correlation $p$ is sensitive to relative phase changes of the anomaly patterns in physical space (Gutzler and Shukla 1984). The larger significance attached to the pattern relative to the magnitude of the anomaly is in concert with usual meteorological intuition. Indeed, several previous investigators used the pattern correlation as a measure of similarity (e.g., Horel 1985; Mo 1986; MG1; MG2).

In order to compute angular PDFs, we normalize each sample map to have a root-mean-square (rms) magnitude 1. In other words, we project every point in phase space onto a hypersphere of radius 1. This procedure may overemphasize minor differences involving samples near the origin. However, as we have seen in Part I (Fig. 8 there), this may not be a serious drawback when considering sufficiently high dimensions, since virtually no sample lies near the origin. In this article, we select dimension four as a reasonable compromise between the requirement of few small anomalies and that of statistical significance.

We define the estimated angular PDF $\hat{f}$ as a function of the solid angle $\omega$ viewed from the origin:

$$\hat{f}(\omega) = \frac{1}{C} \sum_{i=1}^{N} K \left( \frac{\theta_i}{h} \right),$$

where $\theta_i$ is the arccosine of the pattern correlation between sample map $X_i$ and the point $\omega$ at which $\hat{f}$ is to be evaluated, and $h$ is the smoothing parameter measured in radians; $C$ is a constant to ensure that $\int \hat{f} d\omega = 1$. The Epanechnikov kernel $K$ is defined in an analogous way to Eq. (3) of Part I.

In this case, an "adaptive approach" (Part I, section 3b), which varies $h$ slightly as a function of $i$ depending on a preestimated PDF value, is sidestepped for the sake of simplicity. The smoothing parameter $h$ is determined by the least-squares cross-validation (LSCV) technique as described in the Appendix of Part I: we evaluate a scalar, $M_0$ [Eq. (A.4) there], as a function of the smoothing parameter $h$. The $h$ giving a minimum of $M_0$ is expected to give a minimum in $M = \int (\hat{f} - f)^2 d\omega$ in the sense of ensemble averages, as explained in Part I. The LSCV score $M_0$ does not generally show a sharp dip with respect to $h$. It only indicates a certain interval within which reasonable density estimates may be obtained.

b. Bump hunting

In order to find local maxima in a phase space of more than two dimensions, means other than visual inspection are necessary. We employ an iterative algorithm called bump hunting (Fukunaga and Hostetler 1975):

$$x^{(n+1)} = x^{(n)} + \frac{a \nabla \hat{f}(x^{(n)})}{\hat{f}(x^{(n)})}.$$  (2)

The parameter $a$ controls the speed of convergence and is immaterial to the final results. As initial points for the bump hunting, we use samples associated with a local maximum in angular PDF values. Thus, the number of starting points—one for each local PDF maximum—is roughly comparable to the effective sample size. Numerically, the output of iteration (2) may differ from one starting point to another, depending on the convergence criterion or on the smoothness of PDFs. Especially, the discontinuous character of the Epanechnikov kernel [Eq. (3) of Part I] may give rise to small oscillations in PDF on the plateau near the major peaks. Practically, however, this is easily circumvented by retaining only those peaks having PDF values that are maximal in a sufficiently large neighborhood. This screening procedure has the additional advantage that it makes the result even less sensitive to the smoothing parameter. We only retain local peaks whose PDF is maximum in a neighborhood defined by pattern correlation values greater than 0.4. Results are not sensitive to the exact threshold value chosen for this selection criterion.

In principle, we can classify all the samples by the local maximum to which each of them converged. This is equivalent to performing the classification by attractor basins of the PDF. In practice, however, we know that LFV is characterized by intervals with enhanced persistence, alternating with transience (see Fig. 1 of Part I and its discussion, for instance). It may not be meaningful to classify all the sample maps, including those from the latter, transient intervals (cf. also "diffuse cluster" of MG2 and fractal basin boundaries of Grebogi et al. 1987). Thus, we restrict membership in a flow regime associated with
a dominant PDF peak to those samples having small angular distance to the given peak. The regime boundary, or the maximum angular distance from the peak allowed for a member, is determined empirically by requiring the overlaps between neighboring regimes to be minimal.

The classification based on angular (or Euclidean) PDFs is simple enough to be applied to any dataset from geofluids and from nonlinear models for them. In effect, it is similar to classical cluster analysis (e.g., Anderberg 1973), but is conceptually more straightforward. Moreover, the statistical significance of each local maximum can be checked with relative ease against suitably generated random time series. Recently, several authors applied cluster analysis to meteorological and climatological data analysis (Kalkstein et al. 1987; Key and Crane 1986; Legras et al. 1988; MG2; Yarnal and White 1987). MG2 applied a form of it to analyze NH 500-mb anomalies. Molteni et al. (1990) also proposed to use PDFs to identify recurrent and persistent flow regimes, in a subspace of leading EOFs for the zonally asymmetric ("eddy") part of NH 500-mb heights. They relied on usual Euclidean distance as a measure of similarity. Since algorithms of cluster analysis, or any other classification, generally have one or two free parameters, results may vary even for the same dataset. Given the small sample size available to us, comparisons between various algorithms and datasets are vital in order to confirm the objectivity and robustness of the results. Along these lines, we became aware during the reviewing process of the hierarchical clustering work by Cheng and Wallace (1993), which shows results in good agreement with ours for a 500-mb, rather than 700-mb, dataset.

We apply the bump-hunting scheme for angular PDFs to our 700-mb height anomalies. Considering the discussion on regionality in section 3b of Part I and at the beginning of this section, we form regional EOFs in the two sectors, PAC and ATL, and analyze them separately. MG2 and Molteni et al. (1990) performed their analysis on the entire NH. A classification of hemispheric patterns with the current algorithm was presented by Kimoto (1987): it showed good agreement with the results by MG2, who used a different and shorter dataset, as well as a different classification algorithm.

The eigenvalue spectra of the regional, low-pass EOFs show clear gaps between the fourth and fifth modes for each of the two sectors, as shown in Table 1. Thus, we use the first four modes in each sector. This choice is consistent with an observation made in Part I (Figs. 5-7 and discussion thereof) that the first eight NH EOFs, which represent 65% of the variance, may be physically distinct from the subsequent ones and carry most of the LFV, intraseasonal plus interannual, in the data. The four leading EOFs in the PAC and ATL sectors are associated with 60% and 62% of total variance, respectively. Hence, roughly speaking, the four PAC EOFs and four ATL EOFs contribute each about half the NH variance associated with LFV. We use 10-day low-pass filtered principal component (PC) time series in the classification in order to circumvent brief interruptions in the time intervals of membership in a given regime.

4. Classification of recurrent flow regimes

a. Classification results and their stability

Results of LSCV for angular PDFs are shown in Fig. 1. As in Fig. 9 of Part I, LSCV does not pinpoint a sharp optimum for the smoothing parameter, but for both the PAC and the ATL sector the minimum lies at $h = 30^\circ$. We carried out the classification also with $h = 40^\circ$, $50^\circ$, and $60^\circ$ for both sectors; all of these are close to and on the conservative side of the minimum in Fig. 1. We chose to base subsequent analyses on the classification results with $h = 30^\circ$. The separation between local maxima becomes clearer for smaller $h$. The better separation between classes also allows a more suggestive synoptic interpretation of the temporal behavior.

For all $h$ examined, $30^\circ \leq h \leq 60^\circ$, several distinct peaks in angular PDFs were found in both the PAC and the ATL data (after the screening mentioned in section 3b). Specifically, for $h = 30^\circ$, 7 PAC and 6 ATL peaks appear. They are referred to as P1, P2, ..., P7 of PAC, and A1, A2, ..., A6 of ATL in the following. While all the 6 ATL peaks survive up to $h = 50^\circ$, PAC peaks P3 P7 are less robust than others. Separation between local PDF peaks and sensitivity to the smoothing parameter are examined in Figs. 2 and 3 for PAC and ATL, respectively. The abscissa in Figs. 2 and 3 is the angular distance along a continuous curve made up of great-circle arcs, each of which connects a pair of detected peaks in the four-dimensional phase space; recall that we normalized each sample map to have unit magnitude, so that such

<table>
<thead>
<tr>
<th>Mode</th>
<th>PAC</th>
<th>ATL</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>21.2 ± 1.7%</td>
<td>17.3 ± 1.4%</td>
</tr>
<tr>
<td>2</td>
<td>15.4 ± 1.3%</td>
<td>17.0 ± 1.4%</td>
</tr>
<tr>
<td>3</td>
<td>12.0 ± 1.0%</td>
<td>15.0 ± 1.2%</td>
</tr>
<tr>
<td>4</td>
<td>11.2 ± 0.9 (59.8)</td>
<td>12.3 ± 1.0 (61.6)</td>
</tr>
<tr>
<td>5</td>
<td>6.9 ± 0.6</td>
<td>7.7 ± 0.6</td>
</tr>
<tr>
<td>6</td>
<td>5.5 ± 0.4</td>
<td>5.5 ± 0.4</td>
</tr>
<tr>
<td>7</td>
<td>4.7 ± 0.4</td>
<td>4.2 ± 0.3</td>
</tr>
<tr>
<td>8</td>
<td>3.1 ± 0.3 (20.2)</td>
<td>3.9 ± 0.3 (21.3)</td>
</tr>
</tbody>
</table>
a curve lies entirely on the unit sphere, but is not itself a great circle. The peaks are ordered so as to have the nearest regimes side by side; slight changes in ordering (not shown) did not modify substantially the impression of separation between regimes. The ordinate represents the angular PDF value (solid) and its statistical significance (dotted), estimated by a Monte Carlo method.

One hundred sets of random four-vector time series were generated, each of which has the same covariance structure and autocorrelation at a one-day lag as the observed low-pass filtered PCs (without normalizing the rms magnitudes). The significance curves in the figures plot the number of random sets that had smaller angular PDF values than that observed along the abscissa. Figures 2a and 3a are the results with \( h = 30^\circ \), and show clear separations between individual peaks, especially for the ATL-PDF (Fig. 3). The PAC-PDF (Fig. 2) is characterized by two strongly dominant peaks, P1 and P2, which survive for the largest \( h \) value examined, that is, \( 60^\circ \). Other PAC peaks are distinct at \( h = 30^\circ \), but become less pronounced for \( h = 40^\circ \) (Fig. 2b) and larger (not shown). Since the peak at P1 is strongly dominant in PAC, neighboring peaks at P7 and P5 appear more like shoulders, while the peaks at the bottom of the distribution are more salient. P5 disappears for \( h = 40^\circ \), and in constructing Fig. 2b, peak coordinates of P5

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**Fig. 1.** Least-squares cross validation (LSCV) score [Eq. (A.4) of Part I] for angular PDFs.

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**Fig. 2.** Angular PDF values (solid) and their statistical significance (dotted) along a curve connecting local maxima detected by the bump hunting for the PAC sector (a) with the smoothing parameter \( h = 30^\circ \) and (b) with \( h = 40^\circ \). The significance level is obtained by comparing the PDF values computed with the observed and randomly generated PCs. For details, see text.

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**Fig. 3.** Same as in Fig. 2 but for ATL.
taken from the results with \( h = 30^\circ \) are substituted. A peak that gives an anomaly map visually indistinguishable from PS at \( h = 30^\circ \) exists also for \( h = 50^\circ \) (not shown), but peaks P3, P4, and P6 disappear for this value of \( h \).

Despite its insignificant appearance in Figs. 2a and 2b, P7 is picked up distinctly from P1, even for a very large value of the smoothing parameter, \( h = 60^\circ \). The shoulder of the dominant peak, P1, represented by P7, is thus a robust feature. We also note that the significance of angular PDF values around P3 \( \sim \) P7 is noticeably higher than random. Furthermore, the separation between peaks is more distinct for the significance curve in Fig. 2b than the PDF itself. This suggests that the density estimate with \( h = 40^\circ \) is already oversmoothed. For the purpose of describing the temporal evolution of LFV as we shall see below, it is helpful to retain recurrent flow regimes that appear like shoulders or ridges in the PDF topography, not only the isolated peaks.

The ATL-PDF (Fig. 3) is characterized by all peaks being of comparable magnitude. The separation between them is clearer than for PAC. Indeed, all six ATL peaks were picked up by bump hunting with \( h = 30^\circ, 40^\circ, \) and \( 50^\circ \). Only A6 was missed with a very smooth estimate using \( h = 60^\circ \).

In order to check the stability of classification further, we repeated EOF, PDF, and bump-hunting computations using the first 19, the second 18, odd 19, and even 18 years of data, with a constant \( h = 30^\circ \). Comparisons with the standard, 37-year results are made by looking at anomaly patterns represented by the peaks. In essence, the results are consistent with Figs. 2 and 3. P1, P2, and all the ATL peaks are virtually unaltered. The PAC peaks P3 \( \sim \) P7 were subject to small positional changes, that is, the anomaly patterns are slightly modified. In two of the above subsets, one of the original seven PAC peaks, P4 or P5, is missing. In some subsets, one or two additional peaks were found. In only one experiment, the second 18 years for the PAC, the number of peaks was less than the standard 37-year case. Otherwise, we had little difficulty in visually associating those peaks obtained from reduced samples with the ones presented here. So the flow regimes we discuss below are fairly robust, within the given dataset and for the classification algorithm employed.

b. Characteristics of regional flow regimes

For the density peaks with \( h = 30^\circ \), the regime membership criterion was set after several trials to \( 38^\circ (= \text{arccos} 0.78) \), for all the peaks. Only a few days of overlaps between neighboring regimes exist for this value, and the conflict is resolved by associating each map belonging to more than one regime with the closest peak. Out of the total 3330 days, 1725 (PAC) and 1499 (ATL) days belong to one of the regional flow regimes. These correspond to 51.8% and 45.0% of the total sample. The remaining days are left unclassified (see also MG1). Tables 2 and 3 show statistics for the PAC and ATL flow regimes that are labeled as P1 \( \sim \) P7 and A1 \( \sim \) A6, respectively. They are ordered with respect to PDF values for the peaks. Figures in parentheses appearing after the peak PDF values in Tables 2 and 3 list statistical significance levels of the peaks and equal those in Figs. 2a and 3a.

In Tables 2 and 3, \( T_d \) is the average duration in a regime, which is counted from the entrance of the trajectory into the regime to the next exit. Such a time interval is called an event (Ghil 1987). \( T_w \) is called the average wandering time, taken between the exit from the given regime to the next entrance to another regime in the same sector (cf. MG2).

Values of \( T_d \) for the regional regimes are not very large; typically, they range from 4 to 7 days. From the part of the tables listing the number of events with given durations, we see that this is mainly due to the large number of short events, with durations of 1 to 4 days. This is related to the following statistical property of the regime persistence.

We show persistence characteristics in a graphical format in Fig. 4, in which the number of events is plotted against their duration. As in similar plots of Dole and Gordon (1983, hereafter called DG; see their Fig. 8) for their persistent anomalies, we note

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**Table 2. PAC regime statistics. Numbers in parentheses after PDF values (column 2) show statistical significance levels against 100 randomly generated PCs. See text for details including an explanation of \( T_d \) and \( T_w \).**

<table>
<thead>
<tr>
<th>Regime</th>
<th>PDF ( \times 10^2 )</th>
<th>Number of days</th>
<th>Number of events with duration ( \tau ) days</th>
<th>( T_d ) (days)</th>
<th>( T_w )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>( 1 \leq \tau \leq 4 )</td>
<td>( 5 \leq \tau \leq 9 )</td>
<td>( 10 \leq \tau \leq 14 )</td>
</tr>
<tr>
<td>P1</td>
<td>16.7 (98)</td>
<td>424</td>
<td>25</td>
<td>17</td>
<td>9</td>
</tr>
<tr>
<td>P2</td>
<td>11.7 (73)</td>
<td>293</td>
<td>17</td>
<td>14</td>
<td>12</td>
</tr>
<tr>
<td>P3</td>
<td>7.2 (89)</td>
<td>222</td>
<td>19</td>
<td>17</td>
<td>4</td>
</tr>
<tr>
<td>P4</td>
<td>7.1 (95)</td>
<td>213</td>
<td>22</td>
<td>18</td>
<td>2</td>
</tr>
<tr>
<td>P5</td>
<td>6.4 (86)</td>
<td>202</td>
<td>25</td>
<td>12</td>
<td>3</td>
</tr>
<tr>
<td>P6</td>
<td>6.3 (77)</td>
<td>171</td>
<td>20</td>
<td>15</td>
<td>0</td>
</tr>
<tr>
<td>P7</td>
<td>6.2 (74)</td>
<td>200</td>
<td>14</td>
<td>14</td>
<td>2</td>
</tr>
<tr>
<td>Total/mean</td>
<td>1725 (51.8%)</td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>

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no signs of preferred duration. Rather, the curves follow roughly straight lines in the log-linear plot. In this case, the average duration, $T_d$, is equivalent to the exponential decay time. As noted by DG, this property is interpreted as the probability of one event that persisted $n$ days to persist another day being only a very weak function of $n$. Mukougawa (1988; his appendix C) explains this property in terms of locally linearized dynamics in the neighborhood of quasi-stationary points in phase space. Events with relatively short durations ($< 5$ days) correspond to transient passages of the system's trajectory, at a relatively large distance from the center of a regime. Such short passages through the outer reaches of a regime still help to identify the system's preferred transition routes.

We note a slight convexity in the curves of Fig. 4, pointing to a small decrease in the likelihood of continued persistence with duration. This might be due to the smallness of the number of events, compared with the number used by DG, as well as to the sensitivity of the durations to phase shifts in our case. DG counted persistent events at individual grid points, while we refer to the spatial patterns of anomalies. When local, gridpoint values are used to identify persistence of large anomalies rather than flow patterns, the cumulative duration becomes less sensitive to slow movements of the anomaly centers, and estimated durations may become longer. The local approach, however, cannot discriminate between the contribution of different flow patterns to the persistent anomalies at a particular grid point.

In order to examine the synoptic features of the regime flow patterns, we show composite anomaly maps in Figs. 5 and 6. They are formed by averaging unfiltered anomalies over all the samples belonging to each regime. Those grid points that have averaged anomaly values significantly different from zero at 99%, judged by a gridpointwise $t$-test, are shaded. The number of degrees of freedom for the test is conservatively estimated by dividing the number of collected samples by 10, which is greater than the $T_d$ listed in Tables 2 and 3. We have also examined maps reconstructed from each set of four regional
EOFs only, with coefficients corresponding to the PDF peaks (not shown). Their patterns are virtually the same as the unfiltered anomaly composites in the corresponding geographical regions.

We next take a closer look at the synoptic characteristics of the classified flow patterns. The PAC-regime, P1, is the well-known Pacific/North American (PNA) pattern. The composite anomaly map shown in Fig. 5a closely resembles WG's Fig. 17c, which is the difference between positive and negative extremes of their PNA index and is based on monthly mean 500-mb maps. Dole's (1986a) PAC negative composite (his Fig. 1b) looks essentially the same. MG2's cluster 1 (labeled W3; their Fig. 10a) contains the PNA signature, but it resembles better our P7 (see below) in the PAC sector. The P1 pattern is characterized by
a strong zonal flow over the central North Pacific as seen in the composite of total heights shown in Fig. 7a, and a wave train over North America (Fig. 5a). It has the largest angular PDF value and by far the greatest number of members (424 maps) among the PAC regimes.

The PAC-regime P2 lies opposite to P1 (PNA) with respect to the climatological mean. MG2 (their Fig. 10f) and Part I called it reversed PNA or RNA. It is characterized by a well-developed ridge over the central North Pacific. The anomaly pattern (Fig. 5b) and the total composite (Fig. 7b) again resemble WG's Fig. 17c and Dole's (1986a) PAC positive composites, respectively; P2 is the second-largest regime in the PAC sector in terms of PDF and the number of members (293). The appearance of a pair of sign-
reversed patterns like P1 and P2 is assumed a priori in linear correlation analyses such as WG, BL, and Esbensen (1984). We obtained them without any such assumption. The pair of anomaly patterns may or may not be dynamically related.

Regime P3 is characterized by stronger-than-normal westerlies over the North Pacific (the total map not shown), which are shifted considerably to the north compared with P1. The anomaly pattern (Fig. 5c) bears some resemblance to MG2's cluster 5 (labeled WT; their Fig. 10e) in the PAC sector, and to BL's North Pacific (NP) pattern (their Fig. 13), which is reported to be the most visible during transition seasons (that is, spring and fall) but also appears in their

Fig. 6. As in Fig. 5 but for ATL regimes (a) A1, (b) A2, ..., and (f) A6.
shifted to the west of, the “blocked” phase of WG’s western Atlantic (WA) pattern (their Fig. 23).

P5 (Fig. 5e) represents zonal circulations both over the Pacific and over the Atlantic (the total map not shown). The anomaly pattern over the Pacific appears as a northwest–southeast oriented wave train.

The P6 pattern is an omega block over the north-central Pacific (Fig. 5f for the anomaly, and Fig. 7c for the composite of the total field). It can also be seen as a wave train from the central Pacific northeasterward to the western Atlantic with roughly opposite phase to P4 (Fig. 5d). But, the negative center of P4 near Kamchatka is not so accentuated as the center of the “block” in P6. MG2’s cluster 4 (NSO) has a large high near Kamchatka but ours does not accompany another high over Greenland, as theirs does. The dipolar structure of P6 over the North Pacific is reminiscent of the western Pacific (WP) pattern of WG81, but our positive center lies about 20 degrees longitude east of theirs. Significantly reduced high-frequency (2.5 ~ 6 days) synoptic activity is noted inside the blocking anticyclone (not shown here, but see Fig. 20f of Kimoto 1989).

The P7 pattern is characterized by a strongly developed ridge over Alaska (Fig. 7d). The wavy anomaly pattern (Fig. 5g) resembles P1 but with different relative strengths of individual centers, the high over Alaska being dominant in this regime. MG2’s cluster 1 is more like our P7 than P1 in the PAC sector. The limited-contour maps shown in Fig. 2 of Part I are of this regime. A one-point correlation map with (70°N, 140°W) as the base point (cf. Esbensen 1984, his Fig. 8) resembles this pattern. From the PDF cross section shown in Fig. 2, and from transition statistics to be discussed below, we interpret P7 as a variant of the P1 (PNA) pattern. Still, this pattern was always picked up by the bump hunting as being separate from P1.

The ATL-regime A1 is characterized by a deep trough along 40°E, slightly west of Dole’s (1986a) NSU region, together with a strong westerly anomaly over the northeastern Atlantic. The anomaly pattern shown in Fig. 6a resembles BL’s Eurasian (EU) pattern type I (EU1, their Fig. 7). Vautard (1990) also found this pattern (his ZO regime). A significantly enhanced westerly hits northwestern Europe (Fig. 8a). This regime has the highest PDF value and the second-largest number of members (281) among the ATL regimes (Table 3).

The A2 pattern is a wave train extending from the East Coast of the United States northeastward to Scandinavia and on to northern Siberia, with the Scandinavian high being the strongest (Fig. 6b and Fig. 8b). This wave train resembles MG2’s cluster 2 (RW3) in the ATL–EU sector, with appropriate signs. This regime has the largest number of members (316) among the ATL regimes.
Regime A3 is characterized by two large positive anomalies over the North Atlantic and northern Siberia, approximately coinciding with Dole’s (1986a) ATL and NSU key regions. MG2’s cluster 3 (W2) is essentially the same as our A3. Molteni et al. (1990) and Vautard (1990) also found a flow regime that resembles A3 in the ATL sector.

A positive anomaly is centered over Greenland in A4 (Fig. 6d). An elongated negative anomaly extends from south of it into northern Siberia. The standing part of a 40–50-day oscillatory mode in the NH extratropics, discussed by Ghil and Mo (1991), has similar structure in the ATL sector. Vautard (1990) has called this pattern the Greenland anticyclone (GA).
Pattern A5 is an omega block with a high just south of Iceland (Fig. 6e and Fig. 8c). The anomaly pattern is characterized by a strongly localized north-south dipole. This pattern can be regarded as the blocked phase of the North Atlantic Oscillation (NAO) studied by van Loon and Rogers (1978) and others (cf. also Part I). MG2’s cluster 4 is similar to A5 over the North Atlantic. The center of anomalous high in

Dole’s (1986a) ATL positive composite (his Fig. 2a) is located some 15 degrees latitude south of ours. Associated with the notable shrinking in the western North Atlantic (Fig. 8c), high-frequency (2.5 ~ 6 days) synoptic activity is also confined to the region just upstream of the block (not shown here, but see Fig. 21e of Kimoto 1989).

Regime A6 resembles the East Atlantic (EA) pattern

Fig. 8. As in Fig. 7 but for ATL regimes (a) A1, (b) A2, and (c) A5.
of WG and Dole's (1986a) ATL negative composite, with a negative anomaly center located south of Iceland. In MG2's cluster 5 (WT), the wave train feature over northern Europe and Siberia is more evident than here.

Wave train–like features are evident in many of the recurrent flow patterns obtained here. Most of them lie over the Pacific/North American and Eurasian “waveguides” (cf. Fig. 13b of Blackmon et al. 1984a): P1, P2, P4, P6, and P7 over the former and A1, A2, A3, and A6 over the latter. North–south dipolar features are also present (cf. Fig. 13a of Blackmon et al. 1984a).

Some flow patterns in our classification represent regional blockings. They are characterized by large positive anomalies in high latitudes, and include P2, P6, and P7 in the PAC sector and A2, A3, A4, and A5 in the ATL. There are also patterns that are associated with intensified or elongated jet streams, for example, P1, A1, and A6.

It is interesting to note that “omega blocks” occur in the PAC, as well as the ATL sector, namely P6 and A5 (Figs. 5f and 6e; see also Figs. 7c and 8c). Both are characterized by “downstream” features, that is, a low over northern Canada and a weaker high off the west coast of the United States, while A5 is characterized by a pure dipole. The dynamical similarity and dissimilarity between these two flow regimes is an especially intriguing question for further synoptic and dynamical studies.

c. Relations between hemispheric and sectorial regimes

To examine associations between PAC and ATL regimes, we counted first the number of days classified as belonging to PAC and ATL regimes simultaneously. Each such day is called an overlap. Table 4 shows the overlaps between the two sectors. The procedure adopted for statistical significance testing is similar to the one proposed by Vautard et al. (1990) for the tests of transition matrices of the atmospheric Markov chain, as presented also in the next section. We first define an integer–valued time series for each sector by using the appropriate regime number for the member dates and zeros for the transient periods. Next, we generate random time series that have approximately the same number of events with approximately the same average durations for each sectoral regime by shuffling the observed events paired with the succeeding transient period. Simulated numbers of events and durations are not exactly the same as observed, since the discontinuity between one winter and the next was also enforced for the random series. One thousand simulations were performed for each sector, and tables similar to Table 4 were generated for each run. When an entry in the observed table is exceeded by less than 50 simulated ones, it is declared to be more likely than random at a 95% level of significance; significantly unlikely overlaps are defined in an analogous manner. In Table 4, boldface and italic indicate likely and unlikely overlaps, respectively, at 90%. Among them, those exceeding the 95% level are underlined.

First, we note that the fraction of overlapping days within any one regime is not very high. This is seen in the sum of each column or row in Table 4, in contrast to the total number of days in the corresponding regime (listed in parentheses). The ratios are listed in the right- and bottommost sections in the table. Typically, less than half of the total number of days are overlapping. Furthermore, given a particular sectorial regime, more than one regime in the other sector over-

<table>
<thead>
<tr>
<th></th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>A4</th>
<th>A5</th>
<th>A6</th>
<th>Sum (Total)</th>
<th>Sum Total (%)</th>
</tr>
</thead>
<tbody>
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<td>40</td>
<td>20</td>
<td>43</td>
<td>15</td>
<td>31</td>
<td>12</td>
<td>161 (424)</td>
<td>40.0</td>
</tr>
<tr>
<td>P2</td>
<td>19</td>
<td>48</td>
<td>14</td>
<td>13</td>
<td>8</td>
<td>33</td>
<td>135 (293)</td>
<td>46.1</td>
</tr>
<tr>
<td>P3</td>
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<td>10</td>
<td>14</td>
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<td>45.0</td>
</tr>
<tr>
<td>P4</td>
<td>9</td>
<td>12</td>
<td>22</td>
<td>24</td>
<td>8</td>
<td>105</td>
<td>105 (213)</td>
<td>49.3</td>
</tr>
<tr>
<td>P5</td>
<td>25</td>
<td>8</td>
<td>3</td>
<td>7</td>
<td>21</td>
<td>75</td>
<td>75 (202)</td>
<td>37.1</td>
</tr>
<tr>
<td>P6</td>
<td>14</td>
<td>17</td>
<td>15</td>
<td>3</td>
<td>18</td>
<td>25</td>
<td>92 (171)</td>
<td>53.8</td>
</tr>
<tr>
<td>P7</td>
<td>16</td>
<td>18</td>
<td>13</td>
<td>44</td>
<td>6</td>
<td>103</td>
<td>103 (200)</td>
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<tr>
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<td>124</td>
<td>112</td>
<td>104</td>
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<tr>
<td>Sum Total (%)</td>
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<td>59.2</td>
<td>45.9</td>
<td>48.9</td>
<td>48.6</td>
<td>63.0</td>
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</table>
lapses with it. Associations between particular pairs of regimes in different sectors are not particularly evident. Nevertheless, the frequency of some pairings exceeds that due to chance alone. For example, P3 is most likely to appear with A2, while A2 may also appear concurrently with P2. When events with duration shorter than 5 days are excluded, numbers in the table become smaller, but little quantitative change is observed for their significance.

In order to clarify the nature of these intersectoral associations, we show in Fig. 9 the two-dimensional (2D) phase subspace, spanned by the NH (not regional) EOFs 1 and 2 that were used extensively in Part I. Projections of composite anomaly maps in Figs. 5 and 6 onto this plane are indicated by circles. The four rectangles are the regions previously called PNA, RNA, ZNAO, and BNAO in the hemispheric analysis of Part I (see Fig. 18 of Part I for spatial patterns); Z and B stand for *zonal* and *blocked* phases, respectively.

Figure 9 reveals that all but one (A4) of the circles representing the approximate positions in the NH phase space fall inside, or near, the four NH regimes. An inspection of the likely pairs of overlaps in Table 4 reveals that they occur within RNA and BNAO regimes, that is, between those sectorial regimes lying near the RNA or BNAO regions, respectively. No overlap between sectorial regimes associated with distinct NH regimes is likely at the 95% level; the P5–A6 association, which is between ZNAO and RNA, is the only such overlap significant at the 90% level. In fact, all unlikely pairings occur between sectorial regimes associated with different NH regimes. PDF inhomogeneities in the NH EOF plane reflect, therefore, the existence of multiple regional flow regimes.

The four NH regimes thus synthesize rather loosely a larger number of regional flow patterns. The intersectoral preferences seen in Table 4 can be understood as relative closeness between patterns in the phase space spanned by the leading NH EOFs, which point to the most populated regions in phase space (cf. MG1, MG2, and Farrara et al. 1989). To summarize, while we cannot preclude the statistical significance of hemispheric, coherent regimes, they are likely to arise dynamically from a variety of events that exhibit more sectorially confined features.

5. A Markov-chain description of transitions

Once a reasonable classification of flow patterns is obtained, it is interesting to see how transitions among them take place. First of all, we show that the appearance of regional regimes is not concentrated within particular years. The time series shown in Fig. 10 are the pattern correlations between daily positions of the trajectory and the peaks in angular PDFs. Ten win-

![Fig. 9. Projections of composite maps for the PAC and ATL regimes shown in Figs. 5 and 6 onto the plane spanned by the first and second modes of NH EOF. The four rectangles are the same as in Fig. 11a of Part I, and indicate the four NH regimes defined there. Axes are normalized by the square root of the eigenvalue of NH EOF1, which is 25 meters.](image)

ters starting from 1969/70 are illustrated. The first four regional EOFs are used to compute the pattern correlation, and only values over $0.5 = \cos 60^\circ$ are shown. The time intervals during which the curves go above the $0.78 = \cos 38^\circ$ level are those identified as regional regimes and are blackened. The regimes are not ordered by size, but so as to study preferred chains of transitions in section 5b. By visual inspection, we immediately notice that all the regimes appear in multiple years. A slight preference for them to appear repeatedly in certain years can also be noted. Relations between a tropical interannual signal and the extratropical regimes are discussed by Kimoto (1989).

a. Transitions between regimes

Next, we investigate statistical properties of the transitions using a Markov-chain description, as adopted by Ghil (1987), Kimoto (1987, 1989), MG1, MG2, Molteni et al. (1990), Spekat et al. (1983), and Vautard et al. (1990). The transition matrices are formed by counting the number of passages from one flow regime to another, via an unclassified, transient period. We only study here transitions between regimes that are both in the same sector. Tables 5 and 6 show transitions for PAC and ATL flow regimes, respectively. Since our datasets are not long enough to discuss transition probabilities, the entries in the matrices are simply the number of transitions.

As noted by MG1 and MG2, the matrices are far from uniform, indicating that preferred transition routes exist. The most likely transitions are printed
in the tables in boldface and the least likely ones in italics. Significance level is 95% when underlined, and 90% otherwise. The same 1000 simulated random time series as in the previous section were used. We also checked the average wandering time $T_w$ for each transition in Tables 5 and 6 (not shown) and found that $T_w$ among ATL regimes was noticeably longer than among PAC regimes (cf. also Tables 2 and 3). Still, for the most likely transitions, $T_w$ was not so long as to render implausible synoptic or dynamic associations between the two regimes involved in the transition. When events with duration less than 5 days are excluded, the entries in Tables 5 and 6 become much smaller. Furthermore, average wandering time becomes too long to maintain the credibility of sequential associations. Therefore, in order to study the system’s preferred temporal evolutions, it is necessary to take into account also transient passages through the periphery of regimes.

The Monte Carlo testing takes into account the
TABLE 5. Number of transitions between PAC flow regimes. Likely and unlikely transitions at the 90% level are printed in bold and italic type, respectively. Those entries significant at the 95% level are underlined.

<table>
<thead>
<tr>
<th>From</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
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<tr>
<td>P3</td>
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<td>11</td>
<td>6</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>P4</td>
<td>13</td>
<td>8</td>
<td>2</td>
<td>3</td>
<td>4</td>
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<tr>
<td>P5</td>
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<td>6</td>
<td>10</td>
<td>7</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>P6</td>
<td>5</td>
<td>6</td>
<td>2</td>
<td>3</td>
<td>4</td>
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<tr>
<td>P7</td>
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<td>2</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Sum | 56 | 43 | 39 | 38 | 41 | 34 | 34 |

nonuniformity in cluster size (Vautard et al. 1990). Therefore, the largest entry in these tables does not necessarily have the largest significance, if one of the regimes involved has a greater number of members than others. An example for this is the transition from A2 to A1 listed in Table 6. Despite the large number of transitions observed (12), it falls a little short of the 90% level (89%), and, therefore, is not marked in the table.

Transitions between regimes in different sectors were examined by Kimoto (1989). They are omitted here since the ratio of the number of possible transitions (that is, of pairs of regimes) is much smaller than for transitions limited to a single sector (by about a factor of four); thus, the statistical significance of most, but not all, entries in the appropriate transition matrix would be marginal.

Referring to composite maps for the sectorial flow regimes in Figs. 5, 6, 7, and 8, we note intriguing synoptic features in some of the likely transitions. A transition in PAC, P1 → P7, describes a structural change of the PNA wave train. The phases of P1 and P7 are similar, but relative strength between a negative center over the North Pacific and a positive one over Alaska differ considerably (Figs. 5a and 5g). The opposite transition P7 → P1 is also picked up in the transition matrix, which lead us to interpret P7 as a variant of PNA in section 4b. Another transition, P4 → P1, describes a phase shift of PNA-like wave trains (Figs. 5a and d). From Fig. 9, we see that the centers of regimes P1, P4, and P7 lie close to the PNA regime identified in the NH EOF plane.

Similarly, the transition P2 → P6 describes a phase shift between the two RNA regimes (Figs. 5b and 5f). The opposite transition did not occur frequently enough to be significant. Synoptically, this transition corresponds to a westward shift of a positive anomaly center over the North Pacific that leads to the formation of an omega block (P6; cf. Figs. 5f and 7c). From P6, a transition to P5 is most likely, which describes a further westward shift of the positive anomaly to the Sea of Okhotsk (Figs. 5f and 5e). The westward shift of a blocking high in its decaying stage has been noted by many synoptic meteorologists (Namias 1947; Berggren et al. 1949; Rex 1950; Pálmen and Newton 1969, p. 278). Our results suggest that a similar westward shift of a high (or a ridge) may sometimes precede the occurrence of the omega block, P6. The sequence of transitions P2 → P6 → P5 (Figs. 5b, f, e) appears similar to a westward-propagating mode discussed by Kushnir (1987). Branstator (1987) also discusses a retrograding mode in the North Pacific. We further elaborate on this sequence later in this section.

We also found transitions that describe phase and structural changes in wavelike anomaly patterns in the ATL sector. The transition A2 → A1 (Figs. 6a

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TABLE 6. Same as Table 5 but for transitions between ATL flow regimes.

<table>
<thead>
<tr>
<th>From</th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>A4</th>
<th>A5</th>
<th>A6</th>
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<td>A6</td>
<td>8</td>
<td>11</td>
<td>9</td>
<td>5</td>
<td>1</td>
<td>5</td>
<td>39</td>
</tr>
</tbody>
</table>

Sum | 45 | 46 | 44 | 32 | 38 | 34 |
and 6b) is characterized by a phase change in a wave train extending from the North Atlantic to Eurasia. The transition A1 → A3 (significant at the 87% level) can also be viewed as describing changes in relative strength of anomaly centers.

The transition from A6 to A2 has two interesting aspects: the position of the strongest feature shifts downstream, while the phase of the wave shifts one-quarter wavelength upstream. The former aspect is reminiscent of downstream energy propagation by a stationary Rossby wave train. Blackmon et al. (1984b) showed, based on lag-correlation statistics, that such downstream shifts are commonly observed over the North Atlantic–Eurasian domain. Therefore, the region may be called the Eurasian waveguide. The latter aspect, phase retrogression, seems also to be involved in the A3 → A5 transition, which is characterized by the westward shift of a positive anomaly over the North Atlantic that leads to a blocking event (see also Fig. 18 in section 6). Vautard (1990) observes that his Euro–Atlantic blocking regime is preceded by a similar retrogression as well.

b. ATL and PAC circuits

Closer examination of the transition matrices, and of their graphical presentation (cf. Kimoto 1989, Figs. 19 and 24) reveals the existence of chains of likely transitions. Only those chains consisting exclusively of transitions with very high significance are discussed here. A PAC circuit consists of transitions P2 → P6 → P5 → P3 → P2, all significant at the 95% level. Composite maps of unfiltered 700-mb heights for the four regimes in question, some of which are the same as those shown in Fig. 7, are clipped in Fig. 11 to show only the relevant parts of the NH. The circuit appears as an oscillation in the Pacific westerly jet, involving relatively straight and strongly meandering patterns. The anomaly maps show that it also involves a westward shift of a positive anomaly center, as noted earlier in this section, and changes in the horizontal tilt of the anomaly patterns, from northwest–southeast in P2 and P6 to northeast–southwest in P5 and P3 (compare also Marcus 1990, Fig. 35).

It is not possible to find a similar chain in the ATL sector at the same level of significance, but by including two other transitions, A2 → A1 and A1 → A3, significant at 89% and 87%, respectively, one obtains an ATL circuit, A1 → A3 → A5 → A4 → A2 → A1. Figure 12 is the counterpart of Fig. 11 for the ATL circuit. Certain similarities between the two circuits are evident: (i) Both include omega blocks, P6 and A5, respectively. (ii) The position of the single maximum in westerly velocity over the region shifts northward until the omega block is established. In the blocked regime, the westerly jet is located much farther south; it becomes zonally oriented in regimes P5 and A4, respectively. The PAC and ATL circuits

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**Fig. 11.** Composites of unprocessed heights for regimes involved in the PAC circuit. Contour interval is 30 m. Arrows in the panels indicate jet axes inferred from similar composites of geostrophic wind at 700 mb. Directions of transitions are indicated by the arrows outside the panels.
appear to represent a sectorially confined oscillation in the westerlies.

It should be noted that the two chains, ATL and PAC, are both statistical. The circuits do not always complete their cycles in one winter. It is more common that only one or two segments of a circuit appear episodically. Inspection of all pattern-correlation time series, as exemplified in Fig. 10, helps describe the situation. For the PAC circuit, occurrence of a clear sequence in the order indicated is relatively frequent (e.g., in 1956/57, 1961/62, and 1970/71), though some of the curves did not reach a sufficiently high pattern-correlation value at the given time to be classified as regional events of the proper regime. Some complete cycles can also be seen for the ATL circuit, for example, 1949/50 and 1978/79.

Rough estimates of the period of a potential oscillation associated with either circuit are possible by summing up the average durations $T_d$ listed in Tables 2 and 3 and the average wandering times $T_w$ for each transition (not listed). These values are 37.3 days for the PAC and 68.7 days for the ATL circuit. We have also computed them using only $T_d$ and $T_w$ for those occurrences when two successive transitions within a circuit are actually observed. A Monte Carlo significance test was computed for these two-step transitions as well. Although all of the two-step transitions involved in both circuits are significant at 85% or higher, except $A4 \rightarrow A2 \rightarrow A1$ (74%) and $A2 \rightarrow A1 \rightarrow A3$ (65%), the numbers of such transitions observed are so small that little practical confidence can be obtained. The periods for the PAC and the ATL circuit based on two-step transitions only are 37.9 and 61.7 days, respectively. Since the PAC circuit is more statistically significant and robust, the period changes but little and is close to 40 days. A 40-day oscillation whose evolution is similar to the PAC circuit shown here was detected by Ghil and Mo (1991; their Fig. 11) using a completely different approach.

6. Composite analysis of onsets and breaks

It is of considerable interest to see how initiations (onsets) and terminations (breaks) of individual flow

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**Fig. 12.** As in Fig. 11 but for ATL circuit.
regimes take place. We investigate them in this section by a compositing technique following Dole (1986b; 1989), who defined his persistent anomalies in a different manner, however.

The key dates for composites are defined as the first day, for an onset, or the last day, for a break, of an event in a particular regional flow regime. Days before and after the key dates are called day \(-2, -1, 0, +1, +2,\) and so on, with day 0 being the key date. In the following composites, all the cases are summed and averaged regardless of the duration of the event. Discarding events with duration less than 5 days did not alter the resulting synoptic features, including the statistically significant areas, in spite of the number of collected maps being reduced to almost one half.

In Fig. 13 we summarize the distribution of anomaly maps around onsets and breaks. The standard deviation about the average phase-space position at day \(n\) (relative to the key date) for each regional regime was computed. This measures how the phase-space trajectory converges towards or diverges away from the regimes at the key date. In Fig. 13, the solid lines are the average of this quantity over the seven (PAC) or six (ATL) regional regimes and the dotted lines specify plus/minus one standard deviation among the different regimes. We used four regional EOFs in constructing Fig. 13, which is based on Euclidean rather than angular distance. The curves shift upward as we increase the number of EOFs considered, but their shape does not change qualitatively.

The curves remain nearly horizontal until around day \(-4\) for onsets, when they start decreasing to a lower value within regimes. The opposite applies for the breaks. Therefore, it is not expected, in general, that signals with substantial statistical significance appear more than five days before the onsets and after the breaks. As seen in the transition matrix, a flow regime is preceded and followed by a number of other regimes, with intervening transient intervals that are unclassified.

No significant difference between the curves for onsets and breaks appears in Fig. 13. For individual regimes (not shown), the transitions between the two plateaus took place more rapidly by up to a few days for either onsets or breaks. Vautard’s (1990) finding of onsets being more rapid than breaks could not be verified by our consideration of sectorially averaged statistics alone.

Changes in the speed of the system’s trajectory, \(\|dx/dt\|\) around onsets and breaks are examined in Fig. 14. Euclidean distance in phase space between two anomaly maps 2 days apart is used to measure the speed of evolution (cf. Legras and Ghil 1985). The value is assigned to the central day. Four regional EOFs are used to represent the maps, as in Fig. 13, and all the regime events—PAC and ATL—are summarized. The \(\|dx/dt\|\) value on the ordinate is normalized by the time mean and standard deviation of the sector associated with the event. The dashed lines indicate a 95% confidence interval for the climatological mean of \(\|dx/dt\|\). It is seen that regime onsets (blank circles in Fig. 14) are characterized by above-average transience between day \(-2\) and \(+1\), followed by significant persistence after day \(+4\). An analogous comment, with signs reversed, applies to the average picture of breaks (filled circles). Thus, Fig. 14 serves to verify quantitatively a schematic picture of persistent regime events and relatively abrupt transitions prior or posterior to them; it should be noted, however,
that this may not apply, for instance, to the transient passages discussed in connection with Fig. 4.

Next we present and discuss selected composite anomaly maps for the onsets and breaks of regional regimes. Maps for all the regimes are given by Kimoto (1989). In view of Fig. 13, we do not expect to see very strong signals long before or after the key dates. Indeed, most of the composite evolutions are characterized by in situ growth (decay) of anomaly centers a few days prior (posterior) to the key dates, without significant phase changes (cf. Dole 1989). This is observed regardless of the character of the regime patterns, for example, wave train–like or dipolar. It is possible, though, that the appearance of in situ evolution is simply a result of cancellation among different patterns of evolutions (cf. Vautard 1990). In the following, we focus on coherent features of change other than this in situ growth or decay.

We present composites of 10-day low-pass filtered anomalies. Composites of unfiltered heights (not shown) were quite similar to the low-pass filtered ones.

a. PAC regimes

Figure 15 shows the onset of the regime P1. It is preceded by small negative anomaly centers off the west coast of North America and in the Sea of Okhotsk, as seen on day −6 of Fig. 15. By day −4, the former grows in amplitude and is merged with the latter to form an elongated negative anomaly over the North Pacific Ocean. By day 0, the center of negative anomaly is further strengthened and begins to be accompanied by downstream features, that is, a high over western Canada and a low over the east coast of the United States. It is interesting to note that a weak wave train is also seen over the North Atlantic to northern Europe, which was noted for the PNA and RNA regimes in Part I as well. WG also mentioned features in the Atlantic associated with the PNA pattern.

The overall sequences of P1 composites, including those for breaks (not shown), are similar to Dole’s (1986b) “PAC negative” composite. However, an important difference prior to the P1 or PAC negative onset is that the southern part of China, deemed statistically significant by Dole (1986b), was not stressed in our composite. Reproduction of Dole’s composite with our 700-mb dataset (not shown) showed an area of significance similar to, but a little weaker than, Dole’s 500-mb composite. Therefore, it appears that the differences in case selection procedure along with the difference in atmospheric level can account for the difference in precursor patterns. Dole referred to anomalies at a fixed grid point, while we refer to the large-scale flow patterns. Removal of P1 events with durations less than 5 days did not affect the features discussed here.

The composite for the onset of P2 (Fig. 16) is similar but with opposite signs to that of P1. However, an anomaly center over the Sea of Okhotsk and the west–east elongation over the western North Pacific are not apparent. The evolution is not a mirror image of that for P1. As for P1, an Atlantic wave train is also established by day +2. Comments similar to those for P1, regarding the discrepancy with Dole’s PAC positive composites, apply.

Traces of the preferred transitions are seen in both the onsets and breaks for all regimes involved in the PAC circuit (P2, P3, P5, and P6). The decay of the omega block, P6, is shown in Fig. 17. It is characterized by weakening and westward retrogression of the positive anomaly from day −2 to +2. The day +6 map is reminiscent of the P5 pattern (Fig. 5e). In turn, from days −6 to −2 in the onset of P5 (Fig. 18), the retrogression of the high from the Bering Sea to northern Siberia and subsequent establishment of a northwest–southeast oriented wave train characterizing P5 are clearly seen. This sequence is similar to Kushnir’s (1987) for his retrograding oscillatory mode over the North Pacific (see his Fig. 11). In spite of the discrepancy in the estimated period of the “oscillation” (3 weeks in Kushnir vs ~37 days for the PAC circuit here), Figs. 17 and 18 appear to be one of the most recurrent sequences of flow evolution in the North Pacific.

b. ATL regimes

The traces of preferred transitions between ATL regimes were less obvious in their onsets and breaks than those of the PAC ones. This is consistent with the
larger overall average of the wandering time (compare Tables 2 and 3). Transitions A3 → A5 and A5 → A4 were relatively easy to recognize though.

The retrogression of high-latitude features seen in Figs. 17 and 18 also appears in the breaks of P1, P2, P4, P7, and A1 (not shown), and in the onsets of A4 and A5. Figure 19 presents the onset of the A5 regime. A high located over northern Siberia on day −6 expands to the west to settle and grow over Iceland after day −2. In the decaying stage of A5 (not shown) farther, but lesser, westward expansion is seen.

Successive downstream shifts of the strongest anomaly center are seen in the onset and break of many of the wave train–like regimes. This is also noted by Blackmon et al. (1984b) and Dole (1989) and is reminiscent of energy dispersion by two-dimensional Rossby waves on a sphere (e.g., Hoskins et al. 1977). The break phase of A2 (Fig. 20) is a good example; the position of the strongest feature in the wave train shifts downstream toward the east coast of the Asian continent, while the relative phase of the wave train is not changed. The influence of the Eurasian wave train on wintertime atmospheric variability around Japan has long been recognized (e.g., Gambo and Kudo 1983).

We have also examined evolutions of the variance of high-frequency (2.5 ~ 6 days) anomalies, or “storm tracks” (Blackmon et al. 1977), modulated by the low-frequency, large-scale flow changes using a technique similar to Nakamura and Wallace’s (1990). It is seen that the synoptic activity tended to be enhanced just upstream of positive anomaly centers of P2, P6, and A5, prior to their establishment, which is also noted by the authors cited above (not shown here in order to save space). Otherwise no significant precursors for the onsets and the breaks were found in synoptic activities, although they were observed to follow low-frequency changes in position and strength of westerly jets.

7. Concluding remarks

a. Summary

In this two-part study, we investigated 700-mb height anomalies in the Northern Hemisphere (NH) winter. In particular, we examined those flow patterns that appear repeatedly and can persist beyond the life cycle of traveling weather disturbances. This was done by a systematic investigation of phase-

Fig. 15. Composite maps of 10-day low-pass filtered anomalies for onsets of P1. (a) Day −6, (b) day −2, and (c) day +2. Contour interval is 15 m. Shaded areas are statistically significant at 99% level by a pointwise t-test, in which the number of events collected minus one is used as the number of degrees of freedom (DOF) and is indicated in the legend. Meaning of the light and heavy shadings is the same as in Fig. 5.
Fig. 16. As in Fig. 15 but for onsets of P2.

Fig. 17. Composite maps of 10-day low-pass filtered anomalies for breaks of P6. (a) Day -2, (b) day +2, and (c) day +6. Other conventions are the same as in Fig. 15.
Fig. 18. As in Fig. 15 but for onsets of P5.

Fig. 19. As in Fig. 15 but for onsets of A5.
space structure of the atmospheric data, that is, first by identifying interesting inhomogeneities in sample probability density and next by studying the way the system trajectory travels between the regions of high density. In physical terms, local density maxima in phase space correspond to persistent and recurrent circulation patterns. The Markov-chain description of transitions between the patterns unveils interesting synoptic sequences of events. The major results of this study are the following:

(i) Dynamically interesting inhomogeneities in PDFs do not always appear as multiple, well-separated maxima. This is particularly so for two-dimensional (2D) projections, as examined in Part I of this study (Kimoto and Ghil 1993). It is likely that the dominant peak near the climatological mean is due to the 2D projection of a large number of various, unrelated sample maps, which are mostly associated with omitted axes in phase space (see also Mo and Ghil 1988). As shown by Kimoto (1987), inherent multimodality in PDFs becomes more apparent in higher dimensions where, unfortunately, insufficient sample size prevents us from achieving statistical reliability. Nevertheless, physically intriguing inhomogeneity is discernible even in 2D PDFs, which show radially oriented ridges. Such inhomogeneity becomes more apparent when we use subsets of data that focus on parts of the low-dimensional subspace away from the origin.

(ii) By investigating 2D PDFs spanned by the first two NH EOFs, we identified four interesting regions in phase space that exhibit relative PDF maxima. These regions were called PNA, RNA, ZNAO, and BNAO, based on the corresponding flow patterns. The first and last two of these hemispheric flow regimes represent, in fact, regional contrasts between zonal and blocked circulations in the North Pacific and in the North Atlantic, respectively. The two sectors were separated, therefore, in our subsequent work.

(iii) Based on the considerations in (i) and (ii) above, we used angular PDFs that discard information on the magnitude of anomalies but focus on the regional difference in their shape. A bump-hunting algorithm that searches for local PDF maxima, in the subspace of four leading EOFs for each sector, produces a reasonable classification of regional flow patterns. Specifically, we obtain seven regional anomaly patterns in the Pacific (PAC) and six in the Atlantic–Eurasian (ATL) sectors. Furthermore, it was shown in detail how these regional flow regimes contribute to the inhomogeneity noted for the whole NH in (ii) above. Synoptically, the regional patterns identified correspond to strong or weak zonal flows, blockings, and wave train–anomaly patterns.

(iv) Some pairs of flow patterns lie roughly opposite in phase space with respect to the climatological
mean. This is found in our analysis without any a priori assumption.

(v) Transition properties among the regional flow regimes were studied by the Markov-chain description proposed by Ghil (1987) and used by Mo and Ghil (1987, 1988). The transition matrices are highly nonuniform, that is, preferred routes between regimes exist and are followed repeatedly by the system’s trajectory.

(vi) Statistically and synoptically significant chains of transitions were detected in both the PAC and the ATL sector. Both circuits appear as north-south oscillations of regional westerly jets, with zonal and meandering phases.

(vii) Synoptic characteristics of onsets and breaks for the regional regimes were studied by a compositing technique, which revealed the potential importance of several physical processes: 1) downstream energy propagation, perhaps by the Rossby wave dispersion mechanism pointed out by many investigators (e.g., Hoskins and Karoly 1981; Blackmon et al. 1984b; Dole 1986b, 1989); 2) westward phase shifts of both positive and negative anomaly centers in middle to high latitudes, and 3) phase-locked evolutions of wave trains and omega-shaped blocks.

b. Discussion

Low-frequency variability (LFV) in the extratropics has recently motivated extensive research efforts, but its complexity has prevented so far the presentation of a unified picture. What appears to be lacking most is a framework to place partial knowledge on a few special modes into a broader perspective. Our approach is aimed at a synoptic-statistical description of macroscopic, coarse-grained behavior of the extratropical LFV. Inherently, such an ambitious approach suffers from the limited size of datasets in achieving satisfactory statistical significance. We hope to have achieved the highest degree of significance possible under the circumstances, and to have amply clarified the inescapable limitations. In understanding macroscopic statistical behavior of LFV, ideas from nonlinear dynamical systems theory appear to be valuable (Ghil et al. 1991).

A schematic picture of the NH LFV in phase space—inferred from our results—is given by the coexistence of multiple radial directions, pointing to quasi-stationary flow patterns, and of multiple cyclic orbits, representing nearly periodic modes. The latter orbits connect some of the former patterns. Some pairs of recurrent patterns lie roughly opposite with respect to the climatological mean, which might suggest an association with linear instability modes about a climatological basic state (e.g., Frederiksen 1983; Simmons et al. 1983). Linear instability about a fixed-mean flow has difficulty, however, to explain coexistence of multiple modes: linear theory assumes that only the fastest-growing mode—whether stationary or traveling—is observed. A nonlinear theory based on successive bifurcations (Eckmann 1981; Legras and Ghil 1985; Ghil and Childress 1987, chapters 5 and 6; Mukougawa 1988) gives a more coherent picture of coexisting multiple modes of behavior.

Some of the anomaly patterns of regional regimes exhibited wave train-like features. Rossby wave dispersion may well describe the origin of such features (e.g., Hoskins and Karoly 1981). Such wavy features can be interpreted as the response to localized forcing in the tropics, as the result of barotropic energy exchange between the climatological flow and the anomalies (Simmons et al. 1983) or as a resonant, oscillatory response to extratropical topography (Jin and Ghil 1990; Ghil and Mo 1991). Marshall and So (1990) recently proposed yet another interpretation of the wavy patterns as the difference between equilibrated and nonequilibrated states. The former type of state is essentially a nonlinear solution of the inviscid quasigeostrophic potential vorticity equation, or a “free mode” (Branstator and Opsteegh 1989).

During the regime events, the system’s trajectory makes radial excursions away from the origin; that is, anomaly amplitude grows on the average. This seems to indicate the relevance of linear theories based on the climatological basic state, whether amplitude growth be due to instability, resonance, or appropriate forcing. As argued above, this linear approach becomes less plausible the larger the number of separate regimes. An alternative approach arises from nonlinear theory: if one linearizes the system, at or near the boundary between attractor basins, linear instability should point to the nearby attractors [that is, local density maxima of the appropriate invariant measures; for example, Ghil (1987)]. If so, linearization about the climatological basic flow may give a low-dimensional linear subspace in which the system prefers to reside, since our results show that the mean is likely to be close to such a boundary. This interpretation is consistent with recent results of Branstator (1990): he obtained good correspondence between some of the leading EOFs of a GCM simulation and those of a randomly forced linear model that uses the GCM climatology as a basic state.

Linearization around appropriate points in phase space is a powerful ingredient of the nonlinear theory. As mentioned in section 4b, the exponential character (Fig. 4) of regime duration can be deduced from such linearization. Alternatively, such an exponential distribution is also consistent with that of exit times from an attractor basin of a stochastically perturbed nonlinear dynamical system (Grebogi et al. 1983;
Legras and Ghil 1985). A flow regime is a region in phase space where the system prefers to slow down, but will not always do so. When the trajectory passes far from the center or when it is perturbed by small-scale noise, the passage can be quite transient.

In addition to the inhomogeneous nature of the density distribution in the large-scale atmosphere's phase space, we have shown (following Mo and Ghil 1987, 1988) that there also exist preferred routes that the system's trajectory repeatedly follows. These facts conform to the ergodic theory of nonlinear dynamical systems, since invariant measures supported on a system's attractor may be highly nonuniform (Ghil et al. 1991).

The chains of preferred transitions, or circuits, do not always complete their cycles in one winter. It is more common that only one or two segments of a circuit appear episodically. It is quite natural to imagine that no clear oscillation stands out in such a chaotic system as the wintertime extratropical atmosphere. The by now classic, but still heuristic idea of an index cycle (e.g., Namias 1950) has not been sufficiently clarified so far. We may describe the situation in the following way.

A potentially oscillatory mechanism in the large-scale dynamics can be represented, in its pure form, as a closed orbit in phase space. For example, if we could vary some external parameter for the atmospheric circulation, such as the north–south heating contrast, the oscillation is likely to appear first as a limit cycle bifurcating from a stationary solution (Guckenheimer and Holmes 1983; Legras and Ghil 1985; Jin and Ghil 1990) as this parameter increases. As the external parameter is increased further, the system undergoes successive bifurcations (Eckmann 1981; Ghil and Childress 1987), and the original limit cycle may no longer be stable or may even cease to exist as a solution. Nevertheless, its trace may remain as an inhomogeneity of phase-space flow (cf. Fig. 3 of Part I). The system trajectory sometimes visits the neighborhood of this “ghost” cycle to follow it for some time. The underlying cycle may well be a heteroclinic orbit that originally connected several (unstable) stationary solutions. It is possible that some of the flow regimes obtained here are those parts of the destabilized limit cycles where the trajectory slows down.

If the above intuitive picture for a nonlinear system is correct, we may not observe pure oscillations in a highly chaotic part of the system's phase-parameter space, but their trace—albeit weak—can remain in the statistics as studied here. A more focused study of the extratropical oscillation should not be discouraged, therefore, by the fact that we do not observe a complete cycle every winter. Since it is generally difficult to study such a weak signal observationally, mechanistic model experiments should help our understanding of the situation.

The existence of preferred flow regimes and preferred transition routes can help modify predictability theory and its practical applications. The presence of oscillatory modes, in particular, is one of the few hopes for successful extended-range forecasts (cf. also Ghil et al. 1991). In forecasting into this range, the primary concern is not with high-frequency disturbances but with the low-frequency regimes of large-scale flow. At least we may expect considerable variability in the skill of initial value approaches, for example, dynamical forecasts, depending on the degree to which the current regime persists or on whether the first transition is appropriately simulated or not.

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