Dynamic Modeling of the Spatial Distribution of Precipitation in Remote Mountainous Areas

Ana P. Barros and Dennis P. Lettenmaier
Department of Civil Engineering, University of Washington, Seattle, Washington

(Manuscript received 3 January 1992, in final form 28 August 1992)

ABSTRACT

Precipitation in remote mountainous areas dominates the water balance of many water-short areas of the globe, such as western North America. The inaccessibility of such environments prevents adequate measurement of the spatial distribution of precipitation and, hence, direct estimation of the water balance from observations of precipitation and runoff. Resolution constraints in atmospheric models can likewise result in large biases in prediction of the water balance for grid cells that include highly diverse topography. Modeling of the advection of moisture over topographic barriers at a spatial scale sufficient to resolve the dominant topographic features offers one method of better predicting the spatial distribution of precipitation in mountainous areas. A model is described herein that simulates Lagrangian transport of moist static energy and total water through a 3D finite-element grid, where precipitation is the only scavenging agent of both variables. The model is aimed primarily at the reproduction of the properties of high-elevation precipitation for long periods of time, but it operates at a time scale (during storm periods) of 10 min to 1 h and, therefore, is also able to reproduce the distribution of storm precipitation with an accuracy that may make it appropriate for the forecasting of extreme events. The model was tested by application to the Olympic Mountains, Washington, for a period of eight years (1967–74). Areal average precipitation, estimated through use of seasonal and annual runoff, was reproduced with errors in the 10%–15% range. Similar accuracy was achieved using point estimates of monthly precipitation from snow courses and low-elevation precipitation gauges.

1. Introduction

Precipitation at high elevations contributes disproportionately to the water balance of many areas of the globe where there is significant topographic variability. For instance, over 70% of the annual runoff in the western United States is derived from snowmelt from relatively small (less than 25% of total land area) headwater catchments. In such areas, the water cycle is controlled by the duration and distribution of precipitation at high elevations, where local topography plays a governing role with respect to the triggering of mechanisms such as condensation and raindrop or ice nucleation and growth. Under conditions where precipitation initiation and enhancement are dominated by airflow over topographic barriers, a precipitation divide is usually observed upstream of the topographic ridge. Intense, lengthy precipitation events are typical upwind of the ridge, while the magnitude and duration of precipitation events decrease sharply on the lee side: this is often termed the rain-shadow effect (Sumner 1988; Cotton and Anthes 1989).

The motivation for improved understanding of the long-term dynamics of orographic precipitation is in part based on the need for better estimates of the areal and temporal distributions of precipitation, which can best be achieved through improved representations of local orography and atmospheric dynamics. This objective cannot be attained with current atmospheric models, which operate at spatial and time scales too large to resolve orographic precipitation adequately, in the case of general circulation (GCM) and limited-area models (LAM) (Giorgi and Bates 1989), or that are too short to simulate more than a few storm episodes at a time in the case of mesoscale models (Cotton and Anthes 1989). For instance, many 2D and 3D models of orographically induced dynamics reported in the literature use a single bell-shaped mountain as a terrain singularity, with time steps often on the order of a few minutes. Also, such models have usually been developed for the investigation of specific phenomena of atmospheric dynamics in the vicinity of mountains (e.g., dry gravity waves, lee waves), under conditions that may or may not be relevant for prediction of precipitation amounts.

In this paper, we describe a regional Lagrangian model for the continuous simulation of precipitation in areas of extreme topographic relief. The model, which simulates the deformation of wind fields by topographic barriers, transports moist static energy and total water through a 3D finite-element grid. The production of water and ice is governed by thermodynamic...
considerations, while precipitation is parameterized as a sink term, the controlling parameters of which are estimated from surface data. A multiyear investigation of the long-term distribution of precipitation for the Olympic Mountains, Washington, is used to illustrate model performance. The results are validated with gauge precipitation, snow depth, and snow water-equivalent measurements, as well as streamflow records from which areal precipitation is estimated. The model was calibrated and verified for a one-year period (1967), and the seven subsequent years were used for model validation only. In addition, results from the application of the model in predictive mode are illustrated through the generation of quantitative precipitation forecasts for selected storms.

2. Previous work

In an idealized characterization, orographic modulation of precipitation is associated with the adiabatic ascent of air parcels embedded in a zonal synoptic flow, due to the smooth deformation of the streamlines over a blocking topographic profile. This simple scenario rarely occurs in practice, and a regional model of orographic precipitation must account for a realistic interpretation of significant meteorological processes. These processes include cloud physics and terrain-induced deformation of winds. Both of these processes remain the subject of ongoing research, and are far from being fully understood. In addition, the fastest computers presently available are still incapable of accommodating the resolution requirements implied by the representation of small-scale processes (entrainment, drop and ice-crystal formation and growth, among others), which affect orographic precipitation. Therefore, the state of the art for orographic models can be summarized as follows:

(i) flow and thermodynamic variables are externally specified;
(ii) cloud microphysics are extensively parameterized; and
(iii) the ascent of air parcels is assumed to occur adiabatically as a result of linear deformation of the synoptic flow field by the local orographic slope.

The flow and thermodynamic variables required by orographic models are generally provided by GCMs or LAMs (Bell 1978; Gollvik 1984; Nickerson et al. 1986) or are taken more or less directly from radiosonde and balloon observations. In some cases, analytical or quasi-analytical flow models have been coupled with cloud models for the numerical representation of well-controlled meteorological episodes (Hobbs et al. 1973; Gocho 1978; Robichaud et al. 1988). The overwhelming majority of such models has been developed for episodic 1D or 2D simulations, and only a few such applications have been verified against gauge precipitation (Collier 1975; Bell 1978; Speers 1986; Richard et al. 1987; Gollvik 1988; Oki and Koike 1991). In a few cases, validation has been attempted using satellite imagery of long-term snow cover (Bagchi 1982) and, more recently, episodic radar information (Takeya et al. 1989). Most of these research applications have been directed toward sensitivity studies of cloud-microphysics processes (Hobbs et al. 1973; Carruthers and Choularton 1986; Robichaud and Austin 1988) or attempts to establish consistent 1D or 2D physically based or purely statistical regressions among orographic indicators (width, length, slope), wind speed and direction, and measured precipitation (Hendrick et al. 1978; Rhea 1978; Carruthers and Choularton 1986; Peck and Schaake 1990). The latter preclude application to more than one characteristic storm at a time, as they rely on the specification of the direction of the approaching wind. In general, these methodologies work well for individual episodes and along orographic slopes facing incoming storms.

Among the numerous simplifications that have of necessity been employed in the previous models, two stand out because of the governing role they may play, especially at high elevations [e.g., more than 1–2 km above mean sea level (MSL)]:

1) neglecting deep convection upwind of the topographic divide, which becomes important for slow-moving air masses, and
2) the formation of solid precipitation.

The computational cost of including detailed description of these phenomena within the framework of a regional model is excessive for applications that last more than a few events. [For instance, a time step of 50 s was used by Hobbs et al. (1973) and Fraser et al. (1973), and time steps of the order of 1–2 min are routinely used in the forecast models of the National Meteorological Center and the European Centre for Medium-Range Weather Forecasts.] Common practice is the calibration of partitioning coefficients to quantify the separation of condensate into rain and snow above the freezing level of clouds and to account for the enhancement of precipitation due to deep convection in strong storm systems. [For instance, Bell (1978) increased the precipitation coefficient by 20% in lieu of accounting for this effect directly.] Cyclogenesis in the lee side of mountains may be responsible for higher precipitation amounts than would be predicted otherwise by the assumption of linear flow deformation [the Olympic Mountains are such a case, as suggested by Mass (1981)]; but this mechanism has been ignored by the studies reviewed above.

The current state of understanding of orographic precipitation as incorporated in the present generation of numerical models can be summarized as follows:

(i) orographic modulation of rainfall upwind of a topographic divide can reach values that vary from 50% to 85% for low topographic features (hills from tens to
a few hundred meters high) up to more than 200% for high-elevation areas (above 1–2 km) (Browning 1980; Hobbs et al. 1973; Robichaud and Austin 1988);

(ii) for low to moderately high and narrow mountains (half-width less than 10 km), the orographic effect consists of the intensification of preexisting rain from stratiform clouds by means of a seeder–feeder type of interaction with the cap clouds (Gochio 1978; Browning 1980; Robichaud and Austin 1988);

(iii) in the case of rainfall alone (warm clouds), the peak of orographic enhancement lies upwind of the topographic peak, and there is a strong, negative gradient in the lee side. The precipitation maximum and its upwind displacement increase with precipitation intensity (Hendrick et al. 1978; Carruthers and Choularton 1986), although significant amounts of low-level moisture may impact upon atmospheric stability, and in some cases, may completely eliminate orographic modulation (Richard et al. 1987; Robichaud and Austin 1988);

(iv) when precipitation falls in solid form, its distribution over low to moderately high mountains includes a tail that spreads over the lee side, due to improved efficiency of horizontal advection relative to the terminal fall speeds of ice particulates (Hobbs et al. 1973); even in these cases, however, the peak of precipitation usually occurs upwind of the topographic peak;

(v) the dynamics of flow deformation by orography prevail over cloud microphysical processes with respect to the bulk quantification of precipitation (Richard et al. 1987; Robichaud and Austin 1988); and

(vi) precipitation rates show an almost linear dependence upon the horizontal low-level wind velocities (Collier 1975; Bell 1978; Carruthers and Choularton 1986; Richard et al. 1987).

3. Model formulation

The model described herein is based on prescribed atmospheric circulation, including 3D wind fields, temperature, and relative humidity. Time series of these variables can be obtained either from an independent atmospheric circulation model or from observations. The latter data-driven approach was used in the case study discussed in this paper.

a. Basic equations

Adiabatic flow is the fundamental thermodynamic assumption of the model. Under this assumption, moist static energy and total water are conservative and can be used as tracers for the study of the movement of an air parcel in the atmosphere (Cotton and Anthes 1989).

The conservation of moist static energy \( h_M \) can be stated by the following transport equation:

\[
\frac{Dh_M}{Dt} = S(p),
\]

with

\[
h_M = c_p T + L q_v + g z
\]

\[
\frac{D}{Dt} = \frac{\partial}{\partial t} + u \frac{\partial}{\partial x} + v \frac{\partial}{\partial y} + w \frac{\partial}{\partial z},
\]

where the scavenging term \( S(p) \) is a function of the precipitation rate \( p \); and \( T \) and \( q_v \) are, respectively, temperature and water vapor content, \( c_p \) is specific heat, \( L \) is latent heat of vaporization, \( g \) is the acceleration of gravity, and \( z \) is the atmospheric height.

The precipitation rate \( p \) is the only scavenger of moist static energy considered by the model. The precipitable water \( q_p \) is calculated as the excess amount of water that satisfies the continuity of total water \( Q \) under saturated conditions:

\[
\frac{DQ}{Dt} = p
\]

\[
Q = q_p + q_s,
\]

and

\[
q_p = q_i + q_s,
\]

where the subscripts \( s \), \( l \), and \( i \) refer, respectively, to saturation and the liquid and ice phases of cloud water. (A complete list of variables appears in the Appendix.)

Condensation is triggered when an ascending air parcel passes its lifting condensation level (LCL). Although there is no specific treatment of cloud microphysics in this model, a corrective coefficient \( \eta \) was introduced, which modifies the relative humidity conditions for which “effective” supersaturation occurs by acting upon the water vapor content at saturation \( q_s \) (e.g., condensation is enhanced by cooling the environment):

\[
q_s^* = \eta q_s.
\]

This artificial corrective coefficient accounts for such processes that occur at a time scale that is much faster than the one inherent to the model’s range of time steps, and whose effect upon cloud formation and growth is aggravated by orographic lifting. Among others, the conditions that contribute to the signature of fast cloud processes are:

(i) the competing effects of cloud-drop growth by collision or simple condensation according to the regional concentrations of cloud condensation nuclei (CCN);

(ii) the presence of high salt concentrations, which activate drop nucleation through the solution effect;

(iii) abundant drizzle, which in coastal regions is an important agent of CCN activation, while it also plays the role both of seeder and feeder of cloud formation and growth (Bergeron 1960; Wallace and Hobbs 1977; Baker and Charlson 1990).
The corrective coefficient \( \eta \) (\( \eta \leq 1 \) for coastal air when \( Q > q_s, \eta = 1 \) otherwise) depends on the mean regional values of CCN and salt concentrations on the study region.

The depletion of condensed water by precipitation is resolved by a linear relationship of the form:

\[
p = Kq_p,
\]

and

\[
P(x, y, t) = \int_{\xi} p(x, y, z, t) dz.
\]

The parameter \( K \), which varies both in time and space, is estimated from surface records of total precipitation. Rain or snow events are partitioned according to the position of the freezing level (FL) through the study domain and the temperature gradient between 850 and 500 hPa (Murray 1952).

b. Model implementation

The transport of moist static energy and total water is interpreted by the model using a strategy of decoupling Eqs. (1) and (3) into equations accounting independently for transport (pathways 1 and 2 in Fig. 1) and thermodynamics (pathways 3 and 4 in Fig. 1). Conceptually, this means that air parcels are isolated from interaction with the environment (e.g., no precipitation) while they travel between two locations, and precipitation is controlled by a point-release process that is switched on or off as determined by thermodynamic considerations.

The use of this methodology was motivated by the necessity to resolve the difference between the horizontal scales of synoptic motions (on the order of thousands of kilometers) and the orographic updrafts (on the order of hundreds of meters) in the space domain, so that the time scale of precipitation (minutes) can be preserved for long periods of simulation (years). Therefore, Eqs. (1) and (3) are partitioned into two pairs of equations: one for total advection of \( \hat{h}_M \) and \( Q \), Eqs. (8a) and (8b), which account for both horizontal and vertical components, and a second pair, Eqs. (14) and (15), to describe depletion of \( \hat{h}_M \) and \( Q \) by precipitation. The latter is used only when the necessary thermodynamic requirements are met:

\[
\begin{align*}
\frac{D\hat{h}_M}{Dt} & = \frac{\partial \hat{h}_M}{\partial t} + \mathbf{V}_t \cdot \nabla \hat{h}_M = 0 \\
\frac{DQ}{Dt} & = \frac{\partial Q}{\partial t} + \mathbf{V}_t \cdot \nabla Q = 0.
\end{align*}
\]

The initial boundary value problem defined by Eqs. (8a) and (8b) is hyperbolic. This means that the quasi-linear partial differential equation associated with it has three families of characteristic lines in the real domain, which are defined by \((x \pm u_t), (y \pm v_t), \) and \((z \pm w_t)\), respectively. Prognostic applications of Lagrangian methods take advantage of the hyperbolic form of the equations by tracking along the characteristic lines of the solution space the trajectory of a state variable from a point \((x, y, z)\) to a previous position [backward method of characteristics (BMC)]. Due to its high variability, the 3D advection field is well suited to a Lagrangian framework, which allows for the tracking of air parcels at the scale of all three velocity components without numerical compromises.

Accordingly, we implemented Eqs. (8a) and (8b) in the form of a 3D adaptive BMC, which uses a fifth-order Runge–Kutta method to solve for the three characteristic equations:

\[
\begin{align*}
\frac{dx}{dt} & = u(x, y, z, t) \\
\frac{dy}{dt} & = v(x, y, z, t) \\
\frac{dz}{dt} & = w(x, y, z, t).
\end{align*}
\]

Theoretically, the time step in Lagrangian methods would equal the simulation time and, consequently, interpolation in a discretized space would be the exclusive source of error. In fact, we can describe the velocity field defined by \( u, v, \) and \( w \) only in discretized form and not as continuous functions in the solution space. Because the uniqueness of the solutions of Eqs. (8a) and (8b) is only certain within the limits of approximation of the velocity field, the time step in Lagrangian schemes is eventually constrained by the
variability of the flow field itself: the time step cannot exceed the interval during which the assumptions that \(u, v,\) and \(w\) are constant hold. In this case, an adaptive time-stepping procedure was implemented, which reconciles automatically the size of the integration time step with the magnitude of the zonal synoptic wind at 850 hPa. This feature is used to optimize the efficiency and resolution of the model for both average and extreme weather conditions.

A 3D finite-element grid (linear elements with eight nodes) implemented in terrain-following coordinates describes the domain of application. The solution of the system of Eq. (9) predicts the position of nodal air parcels at the beginning of the current time step. The moist static energy and total water of the air parcel are then determined by interpolating among adjacent nodes. Moist static energy and total water are conservatively transported during the time interval of advection but are updated with respect to water content whenever air parcels reach their lifting condensation level. At that height, or above, supersaturation values can be calculated from the distributions of \(h_M\) and \(T\):

\[
q_v = \frac{h_M}{c_p} - c_p T - \frac{g z}{L}
\]

(10)

and

\[
\Delta q_s = q_v - q_s^*.
\]

(11)

Formally, the replacement of \(q_t\) by \(q_t^*\) in Eq. (11) can be interpreted as an adjustment for the fact that a traveling air parcel, which is unsaturated at time \((t - \Delta t)\) and is saturated at time \(t\), must have undergone saturation somewhere in between its previous and current locations. The precipitable water contents above freezing level \(q_t\) and below freezing level \(q_t\) can be readily obtained from the continuity and condensation flux, Eqs. (4) and (11), respectively:

\[
q_{t,i} = Q^t - q_t + \Delta q_s.
\]

(12)

Finally, the rain and snowfall rates are the following:

\[
p_r = K_1 q_t
\]

(13a)

\[
p_s = K_2 q_t.
\]

(13b)

For the time scale typical of the triggering of orographic precipitation \((<1\ h)\), melting of snow as it travels through the atmosphere until it reaches the ground can be neglected (Browning and Collier 1989). The total water content and the moist static energy at the beginning of the new integration interval are obtained from continuity of total water:

\[
Q = Q^t - p_r - p_s = q_t^* + q_t(1 - K_1) + q_t(1 - K_2)
\]

(14)

\[
h_M = h_M^t - L \Delta q_s.
\]

(15)

c. Computational aspects

The finite-element grid constructed for the Olympic Mountains has a total of 2112 nodes and 1575 elements (Fig. 2), with six vertical layers corresponding to the 1000-, 950-, 900-, 850-, 500-, and 250-hPa pressure levels. Figures 3a,b illustrate the quality of the topographic representation in the finite-element grids as compared to the “real” topography obtained from a 3-arc-second (approximately 90 m) digital elevation map (DEM).

The horizontal resolution of the grid is about 10 km. A variable time step ranging from about 10 min to 1 h was used, depending on the 850-hPa wind speed. The model requires an average of less than 5 CPU seconds on an IBM 530-RS6000 workstation to complete one time step (1 year of simulations takes approximately 1 h of computer time).

4. Data analysis

a. Initial and boundary conditions

For a given simulation, initial boundary conditions are established by computing a distribution of atmospheric moisture consistent with the daily values of precipitation observed at the beginning date. The results for the simulation of the excursion of the first weather feature through the application domain (typically 3–4 days) are ignored. By so doing, we eliminate the impact of initial conditions on the global analysis of results. This safeguards us against inconsistencies that might result from mistaken specification of initial conditions, such as the estimation of the spatial distributions of precipitation from a sparse number of point measurements (precipitation gauges).

In the absence of detailed atmospheric circulation information for the study domain, radiosonde data were used for the specification of the boundary conditions. There are three radiosonde stations along the northwest coast of North America that might be relevant to this effort: two out-of-state stations, one in British Columbia and the other in Oregon, and one in-state station at Quillayute (see Fig. 4). These stations are positioned to observe the arrival of weather phenomena approaching, respectively, from north, south, and west. Because precipitation along the northwestern coast of the United States is usually accompanied by westerly and southwesterly winds (Speers 1986), Quillayute was selected as the source of boundary conditions data for our simulations. This is generally adequate for the application to the Olympic Peninsula described here. However, during late spring and summer, when long periods of easterly or southeasterly winds occur, the use of Quillayute data as a reference to impose boundary conditions is inappropriate. Because late spring and summer precipitation are responsible for less than 10% of the annual mean precipitation in the Olympic Peninsula, the precipitation simulated during
those periods was simply omitted from our summary statistics.

During the study period (1967–74), radiosondes were launched from the Quillayute station four times daily, and during the 6-h intervals for which no new data are available, the boundary conditions were kept constant. Clearly, during intense storms, when the model must operate at a time step of a few minutes, significant discrepancies may occur at the level of instantaneous precipitation rates. From the point of view of long-term distributions of precipitation though, the spatial mass balance is altered only minimally by such episodes. Synoptic winds, temperature, and relative humidity data form the radiosonde database. Temperature and relative humidity were used to establish the boundary conditions for moist static energy and total water content. In addition, from the environmental and dewpoint temperature profiles, the distribution of the lifting condensation level for air parcels located at all nodes of the finite-element grid was defined.

b. Wind field

Wind, which is the major dynamic component of the model, governs the transport and distribution of energy over the spatial domain. Following previous investigators (Bell 1978; Gollvik 1984), three distinct, though linearly related, wind field components were considered:

(i) a synoptic contribution linked to the general circulation of the atmosphere,
(ii) a surface contribution associated with the planetary boundary layer, and
(iii) an orographically modulated wind field.

The large-scale horizontal wind field is extracted from radiosonde records at convenient heights (the atmospheric layers in the finite-element grid). Both zonal and longitudinal winds were expanded uniformly over the study area. This is clearly a crude approximation in the vicinity of baroclinic highs and lows, or, especially in the case of the Puget Sound, when mesoscale singularities such as convergence phenomena take place (Mass 1981). On the other hand, this approximation is well within the bounds commonly accepted in GCMs and meteorological forecasting models.

In an effort to attain a better representation of near-surface wind fields, a technique of optimal statistical analysis was applied to the spatial interpolation of wind data available at surface stations. Initially, clustering and principal correspondence analysis (PCA) according to Murtagh and Heck (1987) were used to investigate patterns of similarity among the available sta-
tions, with the objective of building a systematic classification scheme. This preliminary analysis was inconclusive. An alternative approach was then evaluated that identified the characteristics of winds with a probability of occurrence equal to or greater than 50 percent at each one of the locations (see Fig. 2 for wind station locations and Fig. 5 for analysis of normalized results at Bellingham, Hoquiam, Olympia, and Seattle–Tacoma airports). Furthermore, our analysis showed that during fall and winter, the dominant daily wind direction was the same (within 45° octants of the wind rose) for more than 75% of the days on which rainfall occurred.

A further evaluation of temporal consistency among the surface stations and the 850-hPa wind at Quillayute was also undertaken. This allowed us to determine the most frequent local surface winds seasonally. Spatial interpolation of the surface wind field was accomplished using the objective analysis approach of Thiebaux and Pedder (1987) as follows:

$$Y(x, y) = \sum_{i=1}^{n} \alpha_i(x, y)x_i$$  \hspace{1cm} (16a)

and

$$\alpha_i(x, y) = \rho_i(x, y)\omega_i,$$  \hspace{1cm} (16b)

where $x$ and $y$ are, respectively, observed and estimated wind properties (intensity and direction); $\rho_i$ is a correlation coefficient; and $\omega_i$ are weighting factors. The latter were established by mean-square-error analysis applied to the minimization of the difference $\Psi$ between observed and estimated wind properties at the $n$ reference stations.
The vertical component is readily computed by integrating the continuity equation for incompressible fluids over the depth of the finite-element grid:

\[
\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} = -\frac{\partial w^*}{\partial z}.
\]  \hspace{1cm} (17)

Finally, the third component of the wind field is introduced by estimating the effect of orography upon the generation or amplification of the vertical velocity field. Blocking effects and differential advection, deflection, and stratification are ignored by this formulation. The result of this approach is that the flow field appears as if the streamlines were molded to fit the topography. Therefore, the vertical velocity resulting from the deformation of the horizontal velocity fields can be described in terms of the partial orographic gradients \(z_x\) and \(z_y\):

\[
w_o = uz_x + vz_y,
\]  \hspace{1cm} (18)

where

\[
z_x = \left( \frac{\partial z}{\partial x} dx \right) \left[ \left( \frac{\partial z}{\partial x} dx \right)^2 + dx^2 \right]^{-1/2}
\]

and

\[
z_y = \left( \frac{\partial z}{\partial y} dy \right) \left[ \left( \frac{\partial z}{\partial y} dy \right)^2 + dy^2 \right]^{-1/2}.
\]

The total wind vertical velocity at any point results from combining linearly the contributions from Eqs. (17) and (18):

\[
w = w^* + w_o.
\]  \hspace{1cm} (19)

In fact, \(w^* \ll w_o\) (centimeters per second for synoptic-scale motions versus meters per second for the orographic updraft) and finally

\[
w \approx w_o.
\]  \hspace{1cm} (20)

**JANUARY**

<table>
<thead>
<tr>
<th>Bellingham</th>
<th>Hoquiam</th>
<th>Seatac</th>
<th>Olympia</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Diagram" /></td>
<td><img src="image2" alt="Diagram" /></td>
<td><img src="image3" alt="Diagram" /></td>
<td><img src="image4" alt="Diagram" /></td>
</tr>
</tbody>
</table>

**Fig. 5.** Characteristic surface winds with frequencies equal to or greater than 50% in rainy days, during January, at selected stations around the Olympic Peninsula. (a) Normalized wind intensity and (b) wind direction.
c. Calibration and verification data

Daily rainfall records and catchment-average precipitation inferred from streamflow data were the main source of calibration, verification, and validation data. In addition, snow water-equivalent measurements were also used in the validation phase.

As if to confirm the need for a model of orographic precipitation that would allow dynamic interpolation of scarce high-elevation precipitation data, the Olympic Mountains are a typical example of scarcity and inadequate distribution of long-term rainfall gauging stations (Fig. 4). All but one of the stations are located at low elevation along the Strait of Juan de Fuca. Sappho is the highest station at 232 m MSL. The distribution of precipitation stations is clearly inadequate for model validation purposes, because most of the significant precipitation events approach the mountains from the west and southwest, and the precipitation maximum is estimated to occur at about 1800–2000 m MSL (Miller et al. 1973).

The situation does not improve much when high-elevation snow-course observations are included. Long-term snow data have been collected at only three snow-course stations, Hurricane Ridge in the Elwha River basin, Cox Valley in the Morse Creek drainage basin, and Deer Park in the Dungeness River basin, in addition to surveys of glaciers in the Mount Olympus area (Fig. 4). Snow water equivalent is measured manually on a monthly basis from January through May, at which time the snowmelt season is under way.

Calibration and verification of the model results with the available precipitation data were carried out in three steps:

1) estimation of the characteristic rain and snow scavenging rates, $K_1$ and $K_2$, by minimizing the mean square of the difference between model predictions and observations;

2) comparing the areal distribution of precipitation computed by the model to estimated long-term precipitation distributions from a precipitation atlas (Miller et al. 1973), snow-course data, and glacier location; and

3) comparing annual-mean areal rainfall over selected catchments delineated by the U.S. Geological Survey (USGS) with mean catchment rainfall estimated from annual runoff measured from stream gauges.

For this purpose, we concentrated on the Quinault, Hoh, and Elwha river basins (areas of about 500–1000 km$^2$), which are located in the critical north, west, and southwest slopes of the Olympics (Fig. 6a). In addition to the use of streamflow data, indirect measurements of precipitation including snow depth and snow water equivalent were used for mass-balance control and long-term seasonal validation of model performance.

Storm predictability was analyzed with respect to interstorm arrival times, time to peak, peak magnitude, and duration. A major storm at the end of January 1967 was investigated in detail and was used to evaluate the model's ability to simulate extreme conditions.

5. Results

Model calibration was carried out for low elevations by using precipitation data collected at the eight low-elevation precipitation stations shown in Fig. 4 and for high elevations by matching seasonal and annual precipitation inferred from runoff for the Hoh, Elwha, and Quinault river basins, and snow-course observations at Hurricane Ridge, Cox Valley, and Deer Park. Relevant statistical properties of the data are summarized in Table 1. Daily and accumulated precipitation for 1967 were used for initial calibration. The streamflow data were used to investigate the performance of the model for high elevations. Point precipitation, catchment average precipitation, and snow-course observations for the period 1968–74 were subsequently used for model verification. When the model was used in predictive mode, special emphasis was placed on the verification of long-term seasonal means at all stations for both precipitation and runoff, and the evaluation of storm properties (interarrival times, duration, and precipitation maxima).

a. Calibration

The initial phase of the calibration process was aimed at finding an adequate description of the spatial variability of the rate of extraction of atmospheric water at all times (e.g., a characteristic distribution of hydrometer scavenging over the study domain). A major
TABLE 1a. Mean and standard deviation of monthly precipitation: winter and fall 1967–74 (see Fig. 4a for station locations).

<table>
<thead>
<tr>
<th>Stations</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>325.1</td>
<td>256.5</td>
<td>254.0</td>
<td>383.5</td>
<td>386.1</td>
<td>63.5</td>
<td>119.4</td>
<td>475.0</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>124.5</td>
<td>129.5</td>
<td>121.9</td>
<td>177.8</td>
<td>177.8</td>
<td>33.0</td>
<td>53.3</td>
<td>188.0</td>
</tr>
<tr>
<td>February</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>215.9</td>
<td>175.3</td>
<td>157.5</td>
<td>322.6</td>
<td>307.3</td>
<td>30.5</td>
<td>63.5</td>
<td>350.5</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>124.5</td>
<td>81.3</td>
<td>78.7</td>
<td>172.7</td>
<td>119.4</td>
<td>12.7</td>
<td>30.5</td>
<td>170.2</td>
</tr>
<tr>
<td>March</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>195.6</td>
<td>165.1</td>
<td>139.7</td>
<td>266.7</td>
<td>241.3</td>
<td>35.6</td>
<td>58.4</td>
<td>297.2</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>81.3</td>
<td>68.6</td>
<td>55.9</td>
<td>99.1</td>
<td>83.8</td>
<td>15.2</td>
<td>22.9</td>
<td>94.0</td>
</tr>
<tr>
<td>October</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>218.4</td>
<td>167.6</td>
<td>182.9</td>
<td>309.9</td>
<td>271.8</td>
<td>43.2</td>
<td>73.7</td>
<td>350.5</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>106.7</td>
<td>81.3</td>
<td>94.0</td>
<td>114.3</td>
<td>106.7</td>
<td>25.4</td>
<td>43.2</td>
<td>150.0</td>
</tr>
<tr>
<td>November</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>297.2</td>
<td>231.1</td>
<td>223.5</td>
<td>363.2</td>
<td>348.0</td>
<td>53.3</td>
<td>94.0</td>
<td>429.3</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>73.7</td>
<td>83.8</td>
<td>81.0</td>
<td>83.8</td>
<td>99.1</td>
<td>22.9</td>
<td>35.6</td>
<td>114.3</td>
</tr>
<tr>
<td>December</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>330.2</td>
<td>215.9</td>
<td>223.5</td>
<td>452.1</td>
<td>348.0</td>
<td>50.8</td>
<td>91.4</td>
<td>469.9</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>81.3</td>
<td>58.4</td>
<td>61.0</td>
<td>91.4</td>
<td>58.4</td>
<td>15.2</td>
<td>17.8</td>
<td>160.0</td>
</tr>
</tbody>
</table>

The objective of this phase of the work was to accomplish calibration without compromising the applicability of the model to special atmospheric conditions or regional features. Hence, a methodology was developed that is based on rules that will be consistent with future applications of the model to other regions. The approach relies exclusively on topography and synoptic temperature and humidity fields.

Based on the results from past studies of orographic distribution of precipitation, the following master relationship was tentatively defined among surface elevation \( h \), local updraft \( w_l \), and relative position in a mountain slope:

\[
K_l = \beta_l w_l \tag{21}
\]

and

\[
\beta_l = \frac{\beta_m^n}{z_{ref}} \tag{22}
\]

where \( \beta \) is the orographic enhancement function, the subscript \( l \) refers to the atmospheric layer; \( \beta_m \) is the maximum orographic enhancement; and \( z_{ref} \) is the elevation at which maximum precipitation is estimated to occur. For a given calibration period, the optimization process consists of searching for values of \( \beta_m \) that result in the best simulations of fall, winter, and spring precipitation. Because of the high frequency of easterly winds during summer and because summer precipitation is mainly driven by convective activity associated with solenoidal convergence originated by mountain-valley gradients of radiative forcing, which is not represented in the model, no attempt was made to calibrate for summer conditions. Nonetheless, the results obtained describe the observed rainfall well for most of the calibration and verification periods (including summer), mainly due to the prevalence of dry weather during late spring and summer (Fig. 7).

Equation (22) suggests, consistent with the model dynamics, that the local elevation can strongly affect the magnitude and evolution of precipitation. Also, mountain blocking of synoptic circulation may have significant impact upon the spatial distribution of moisture availability in the surrounding atmosphere (Pierrehumbert 1984). Despite continuous improvements in the resolution of atmospheric models, aliasing of low elevations cannot be avoided in discrete representations of the earth's orography; for instance, a regional model such as the one described by Giorgi and Bates (1989), which has a resolution of 60 km, fails to represent the Olympic Mountains at all. While our model is of considerably finer resolution (<10 km), the effect of elevation aliasing is still significant as shown in Table 2, where actual elevation data at individual precipitation stations is compared with the gridded elevations of our finite-element mesh. To counteract this effect, a spatial filtering scheme was developed through which a 3D correction surface is fitted to the application domain. Local slope \( I \), distance to the oceanic boundaries \( D \), and aliased elevations \( Z \) are combined linearly to define the mapping function \( F(I, D, Z) \):
The weighting factors $a_i$ are computed by matching selected points: natural choices are the precipitation and streamflow gauges or snow-course stations.

The use of low-elevation precipitation data in this study results from the lack of alternative data sources (high-elevation precipitation gauges). Besides the orographic disparity associated with topographic aliasing, other important effects inherent to mesoscale coastal phenomena, such as land and sea breeze, which are neglected in this model, may interfere with calibration. Scaling arguments presented by Rotunno (1983) indicated that where the Coriolis coefficient $f$ is larger than the diurnal frequency of radiative heating and cooling $\omega_d$, such circulations are relevant over a distance $L$ from the coastline, which can be estimated given a characteristic Brunt–Väisälä frequency $N$ and the vertical length scale of heating $H$:

$$L_w = NH(f^2 - \omega_d^2)^{-1/2}.$$  \hspace{1cm} (24)

In the case of the Olympic Mountains, the length $L_w$ extends about 30 km from the coast for average conditions. This implies that all the precipitation gauges used in this application are within the area of influence of land and sea-breeze phenomena. Synoptic information on relative humidity and temperature fields was used to establish a set of three adjusting filters applicable to dry and wet and cool and hot weather conditions in the Olympic Peninsula. These filters have the structure presented by Eq. (25), where $\mu_x$ and $x_{\text{min}}$ are, respectively, the mean and the minimum observed precipitation at the individual stations, and $x$ is an instantaneous model result:

$$F(\mu_x, x_{\text{min}}, x) = b_1\mu_x + b_2x_{\text{min}} + b_3x.$$  \hspace{1cm} (25)

The weighting coefficients $b_i$ were estimated for a variety of scenarios characterized by dewpoint temperatures $T_D$ above and below 3°C, and the number of days with below freezing-level temperatures.
For this case study, the adjustment parameter $\eta$ was made equal to 0.95 and the orographic enhancement parameter $\beta^\prime$ assumed values equal to 1.5 and 1.0, for $T_D$ above and below 3°C, respectively. Major obstacles to the calibration process were encountered for days during which northerly frontal systems or easterly winds were present. In fact, the problems found are not a consequence of the weather features per se, but result from the poor description of the boundary conditions in such occasions.

Consider first the case of frontal systems. The arrival and evolution of a frontal system in the third week of January 1967 is stylized in Fig. 8 and will be used to illustrate the discussion. Radiosondes launched from Quillayute, which provide point measurements at selected atmospheric heights, fail to provide information on the thermodynamic (temperature and humidity) gradients and wind-field discontinuities that characterize the presence of a front. From our example, in the first day the radiosonde does not "see" the frontal system through a large extent of the lower troposphere. Hence, a delay is expected to be observed in the comparison between data and storm arrival times at the northern stations, which the frontal system has already reached. On the other hand, in the second day, the reverse is true for the southern and eastern areas of the study domain, where the front has yet to arrive. This deficiency in the timing of the specified boundary conditions translates quantitatively into phase errors of model-predicted storm arrivals. However, another difficulty may arise with respect to the magnitude of the storm peak: precipitation will be lower than expected at the northern stations in the first day and higher at the south and easterly stations in the second day. In practice, this may result in the amplification of low precipitation values and reduction of storm peaks for locations in front of and behind the frontal system, respectively. In this context, the use of radiosonde data to impose boundary conditions should be restricted to the area of influence of the radiosonde only, and modeling of large areas necessarily implies one of the following:

(i) the availability of a large number of radiosonde stations, ideally one at or in the vicinity of each boundary node in the numerical grid;
(ii) the coupling of a transport model such as the one depicted in this paper with a regional circulation model, whose role is to interpolate sparse information through physical operators.

In the case of easterly winds, the most important issue relates to the nature of the boundary conditions: for northerly, westerly, or southerly winds, the boundary conditions perform as forcings that activate and induce transport; and for easterly winds, the boundary conditions constitute anchor points for verification of the transport solution. This type of boundary condition has the potential to induce artificial reflection, which may lead to the generation of spurious waves in the transport solution near the boundaries. This problem can be avoided if the grid is extended significantly outside of the area of interest. However, computational considerations preclude arbitrary expansion of the spatial domain without affecting model resolution. For this reason, an alternative approach of simply replacing the spatial distribution of precipitation inferred from the statistics of historical observations on the limited days when the synoptic winds were easterly was used. The same statistical objective analysis scheme used for estimation of surface wind fields was applied to determine the precipitation distribution on days of easterly winds. Normalized distributions of precipitation, such
Fig. 10. Comparison of observed and simulated monthly mean precipitation at the location of the eight precipitation gauges shown in Fig. (4) and for the study period (1967–74): (a) Clallam Bay, (b) Lake Sutherland, (c) Elwha, (d) Neah Bay, (e) Sappho, (f) Port Angeles, (g) Sequim, and (h) Forks.
as the one depicted in Fig. 9 for winter conditions, were found by applying optimal objective analysis with a spatial correlation field \( \rho'(x, y) = \rho(x, y) \) in Eq. (16b) modulated with the surface orographic-enhancement function \( \beta_i \) described in Eq. (22):

\[
\rho'(x, y) = \beta_i \exp[(x^2 + y^2)^{-1/2}/x_L],
\]

(26)

where \( x_L \) is a correlation length, which we took to be 200 km. The precipitation stations are far enough apart that the interstation correlations are relatively small (less than 0.3), which is a necessary condition for application of optimal spatial objective analysis.

Daily and accumulated precipitation values were used to calibrate the model at low elevations, while the catchment water balance, involving streamflow \( R \), total precipitation \( P \), and evapotranspiration fluxes \( E \), was used to infer model performance at higher elevations:

\[
P - R - E = \Delta S,
\]

(27)

where \( \Delta S \) is the change in catchment water storage (as snow water equivalent or soil moisture storage). On an annual basis, especially using the water year October–September, \( \Delta S \) can be taken as zero.

The estimation of evapotranspiration is a difficult problem: adequate meteorological data are available only at Quillayute (elevation 60 m) in the Olympic Peninsula. However, there is a meteorological station at Stampede Pass (elevation 1200 m) in the Cascade Mountains, which can be used to approximate evapotranspiration at roughly similar elevations in the Olympic Mountains. It was found that, for a typical hydrological year (1967) — with a Bowen ratio of 0.9 (typical of the latitude and climate of the Olympic Mountains) and assuming that soil moisture was not limiting — the evapotranspiration calculated according to Arya (1988) was approximately 650 mm at Quillayute and 900 mm at Stampede Pass. The main goal was to verify the water balances of selected river basins on an annual basis. For this purpose, a value of 650 mm for the actual evapotranspiration was assumed, with uniform spatial and temporal distributions during late spring and summer.

b. Validation and storm forecast

Figures 10a–h compare the monthly mean total precipitation simulated by the model and the observed station values. The annual distribution of monthly mean precipitation maxima in the Olympic Peninsula as compared to the observed monthly mean precipitation at Forks is shown in Fig. 11, which illustrates the enhancement effect of precipitation by orography, as well as the consistency of model simulations with respect to the regional seasonality. Table 3 provides a quantitative evaluation of the performance of the model not only for the simulation of long-term annual means, but also for seasonal values, for example, spring.

Table 3. Percentage errors in simulated monthly precipitation for years 1967–74 [expressed as (simulated − observed)/simulated].

<table>
<thead>
<tr>
<th>Stations</th>
<th>Spring</th>
<th>Winter-Fall</th>
<th>Annual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clallam Bay</td>
<td>+17.5%</td>
<td>+3.5%</td>
<td>+5.5%</td>
</tr>
<tr>
<td>Elwha</td>
<td>+12.5%</td>
<td>-1%</td>
<td>1%</td>
</tr>
<tr>
<td>Lake Sutherland</td>
<td>-4%</td>
<td>+5%</td>
<td>0</td>
</tr>
<tr>
<td>Neah Bay</td>
<td>-11%</td>
<td>+3%</td>
<td>-2%</td>
</tr>
<tr>
<td>Sappho</td>
<td>-10%</td>
<td>+8%</td>
<td>-9%</td>
</tr>
<tr>
<td>Sequim</td>
<td>-9%</td>
<td>+7%</td>
<td>-3%</td>
</tr>
<tr>
<td>Port Angeles</td>
<td>+10%</td>
<td>+8%</td>
<td>+4%</td>
</tr>
<tr>
<td>Forks</td>
<td>+16%</td>
<td>+7%</td>
<td>+5%</td>
</tr>
</tbody>
</table>
winter, and fall combined. There is good agreement between observed and simulated data, suggesting that
the anialising and the postprocessing filters are consistent with the dynamics of the predominant physical
processes in the low regions.

Table 4 contains information relative to frequency, duration, and magnitude of storms at the four stations
located farther away from the coast: Forks and Sappho in the west side and Elwha and Lake Sutherland in
the north side. The errors are relevant for the two westside stations, both for storm timing and peak values.
Some of the errors are attributable to the convention used for specification of storm events: precipitation below
0.5 mm day$^{-1}$ was considered negligible. This threshold appeared to be adequate for the northern
stations, but not in the case of western stations, for which the simulated time series of storm occurrence
are characterized by long tails with very low precipitation intensities. Also, the postprocessing filter did not
perform well with respect to the peak storm precipitation at Forks and Sappho. The time evolution of
precipitation during the winter season of 1967 is shown in Fig. 12, for both observed and simulated data. In
particular, analysis of the period corresponding to the storm of 19 January (Julian day 19), which is referred
to in the storm data and unusual weather phenomena (U.S. Weather Bureau 1967), indicates that the storm
peak is underpredicted by the model, while the phase error is about 1 day for these two stations. The peak
error for this large storm is somewhat typical: in general, the model tends to attenuate large storms, and
magnify the more frequent, lesser ones. Phase errors are mainly related to the identification of approaching
frontal systems as discussed above.

The most important goal of the validation process was to investigate the distribution of precipitation in
the high mountainous areas, for which both snow-course and streamflow records are surrogates in an
integrated areal sense. The results for snow-course stations are summarized in Table 5. As is apparent from
Fig. 4, the three snow-course stations are located in the northwest lee side of the mountains, where the
rainshadow effect is significant. Although no direct measurements were available for the glacier regions
during the simulation period, it can be seen that the location of precipitation peaks in model simulations
coincides with the locations of the perennial glaciers.

Table 5. Percentage errors in accumulated precipitation as estimated at high-elevation snow-course stations: (a) January–May 1967, (b) January–May 1968, and (c) January–May 1969 [expressed as (simulated − observed)/observed].

<table>
<thead>
<tr>
<th></th>
<th>Observations</th>
<th>Model Results</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(mm)</td>
<td>(mm)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(a)</td>
<td>(b)</td>
<td>(c)</td>
</tr>
<tr>
<td>Cox Valley</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a)</td>
<td>171</td>
<td>155</td>
<td>-10%</td>
</tr>
<tr>
<td>(b)</td>
<td>357</td>
<td>337</td>
<td>-6%</td>
</tr>
<tr>
<td>Deer Park</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a)</td>
<td>360</td>
<td>347</td>
<td>-3.6%</td>
</tr>
<tr>
<td>(b)</td>
<td>181</td>
<td>179</td>
<td>-1.4%</td>
</tr>
<tr>
<td>(c)</td>
<td>186</td>
<td>256</td>
<td>+37.5%</td>
</tr>
<tr>
<td>Hurricane</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ridge</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a)</td>
<td>422</td>
<td>458</td>
<td>+8.6%</td>
</tr>
<tr>
<td>(b)</td>
<td>211</td>
<td>181</td>
<td>+16.7%</td>
</tr>
<tr>
<td>(c)</td>
<td>363</td>
<td>352</td>
<td>-2.8%</td>
</tr>
</tbody>
</table>

Table 6. Percentage error in simulated precipitation for the Hoh, Quinault, and Elwha river basins [expressed as (simulated − observed)/observed].

<table>
<thead>
<tr>
<th></th>
<th>Hoh</th>
<th>Quinault</th>
<th>Elwha</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Winter</td>
<td>Annual</td>
<td>Winter</td>
</tr>
<tr>
<td>1967</td>
<td>+15%</td>
<td>+3%</td>
<td>+20%</td>
</tr>
<tr>
<td>1968</td>
<td>+45%</td>
<td>+10%</td>
<td>+46%</td>
</tr>
<tr>
<td>1969</td>
<td>+3%</td>
<td>+5%</td>
<td>5%</td>
</tr>
<tr>
<td>1970</td>
<td>+30%</td>
<td>+4%</td>
<td>33%</td>
</tr>
<tr>
<td>1971</td>
<td>+57%</td>
<td>+13%</td>
<td>+7%</td>
</tr>
<tr>
<td>1972</td>
<td>+77%</td>
<td>+2%</td>
<td>+27%</td>
</tr>
<tr>
<td>1973</td>
<td>+28%</td>
<td>+9%</td>
<td>-16%</td>
</tr>
<tr>
<td>Mean</td>
<td>+36%</td>
<td>+7%</td>
<td>+25%</td>
</tr>
</tbody>
</table>
The three catchments used in this study were identified in the numerical grid by the elements from which water drains toward the outlet streamflow station (Fig. 6). The basin areas match the USGS estimated areas within 5% for the Hoh and Elwha river basins, and 10% for the Quinault river basin. The total precipitation $P$ over a watershed was evaluated as follows:

$$P = \int_t \left[ \sum_{i=1}^{n} \int_{\Omega_e} p(x, y, t) \, dx \, dy \right] \, dt,$$  \hfill (28)

where $n$ is the number of finite elements of area $\Omega_e$ within the watershed, and $t$ is the integration period. This analysis was carried out on a seasonal basis, and the results are presented in Table 6. In this case, the seasonal errors are consistent with the seasonal snow melting and accumulation: the apparent winter errors are positive, and in summer (results not shown), the apparent errors are negative. Neither snowmelt nor snow accumulation, $\Delta S$ in Eq. (27), were accounted for in our calculations. Therefore, phase errors such as the ones identified at the end of winter are unavoidable, and it is best to focus on the annual errors. Years with large errors, for example, well above 20%, are mostly
associated with atmospheric conditions characterized by abnormally low dewpoint temperatures, for which the model exhibits less sensitivity as compared to conditions characterized by normal or high dewpoint temperatures. This is the case for the dry winter seasons of 1968, 1971, and 1972. The errors are magnified for the Hoh and Quinault river basins, because the hydrological behavior of these basins is strongly regulated by what happens in the alpine areas. However, the observed annual totals are matched by model simulations with an error of less than 15%. This close agreement is promising for applications of the model to hydroclimatological studies.

Figures 13a–e show the mean monthly spatial distribution of precipitation for the months of January, March, May, November, and December, as obtained from the eight years of model simulation. The orographic effect of the Olympic Mountains upon the regional distribution of precipitation is reflected in the dramatic increase of precipitation with elevation, which can be as much as 200% at the highest elevations. Because the dominant direction of storm approach in the winter months is from the southwest, the orographic enhancement on the upwind side of the mountains is well illustrated by Figs. 13a,b and 13d,e (January, March, November, and December): some low-lying
ridge crests toward the southwest receive nearly as much precipitation on average as the upwind side of the highest peaks. During the spring months, storm directions are more variable (as reflected by Fig. 13c for May) but the southwesterly dominance begins to be reestablished in the late fall (see Fig. 13d for November).

Interannual variability of the spatial distribution of precipitation is illustrated by Figs. 14a and 14b, which allows evaluation of such variability through comparison of the precipitation distribution during February of 1967, with the same month of 1969. The "patchy" appearance of the spatial distribution of precipitation during February 1969 indicates that storm activity was significantly larger during that period than during the corresponding month of 1967, which can be confirmed through the atmospheric records. An important aspect of these results is that, although the spatial distribution of precipitation is distinct for each of the hydrological years, the location of the precipitation maxima remains the same.

6. Discussion

An earlier approach to modeling orographic precipitation (Barros and Lettenmaier 1990) consisted of simulating Eulerian transport of vapor and liquid water. The thermodynamic mechanisms were implemented according to penetrative parcel theory modified by entrainment and precipitation, the rate coefficients for which were estimated through calibration. The model, which is based on a fully implicit scheme, was abandoned due to excessive computational costs. The model formulation described in this paper is close to the convective adjustment scheme described by Cunningham and Mitchell (1990), who suggested that, in climate models, such a scheme transports heat and moisture less efficiently than penetrative parcel schemes. We experienced the same results with respect to the production of precipitation in mountainous regions.

We conducted sensitivity analysis to evaluate the importance of the model time step. Because of the interactions between synoptic circulation and local orographic features, it was concluded that the time step should be allowed to vary spatially. This is illustrated qualitatively in Fig. 15a: larger errors are observed for lower-frequency storms and for easterly winds, which both reflect an inadequacy of the boundary conditions used as well as a gross representation of atmospheric dynamics. At a given station, the error surface expressed as a function of local slope and time step has a bell shape.

![Fig. 14. Monthly precipitation for selected simulation periods: (a) February 1967, and (b) February 1969.](image)

![Fig. 15. Qualitative analysis of spatial and temporal variability of error associated with the time-integration process: (a) as a function of frequency of storm arrival and time step, and (b) as a function of local slope and time step.](image)
shape tilted toward the origin (Fig. 15b). At the origin, the error equals the interpolation error, which decreases as the time step increases up to the point when scaling error, intrinsic to the simulation of physical processes, take over and increase theoretically to infinity.

7. Conclusions

We have developed, implemented, and applied a 4D Lagrangian model to simulate orographically induced precipitation. The model is designed to allow estimation of the long-term hydroclimatological processes of large regions characterized by complex, inaccessible terrain, and to reproduce the properties of individual storm events. It was tested for the Olympic Mountains, with success. We believe that coupling of the model to a spatially distributed surface-energy model is desirable to improve the verification of the hydrological balance throughout the spatial domain, and this is an improvement we intend to pursue.

Subgrid-scale processes such as blocking, thermally forced circulations, lee-side cyclogenesis, and lee waves are not considered in the present form of the model. Hence, although long-term properties of the spatial distribution of precipitation are preserved in model simulations, local effects of mesoscale and field-scale circulation phenomena cannot be reproduced. Assessment of climate change at the catchment scale and the forecasting of extreme events are among the promising fields for the use and further development of the model.

Acknowledgments. We thank two anonymous reviewers for their careful and insightful comments. We are also grateful to Mr. Lance Vail of Battelle Pacific Northwest Laboratories; Mr. Larry Nickey of the U.S. National Park Service; Olympic National Park; and to Mr. Ernie Recker and Mr. Mark Albright from the Atmospheric Sciences Department, University of Washington, for assistance in the acquisition of the radiosonde, precipitation, and snow-course data used in this study. The research reported herein was supported in part by the National Aeronautics and Space Administration under a Global Change Fellowship award to the first author, by Pacific Northwest Laboratories under Contract DE-AC06-76RL0 1830 with the U.S. Department of Energy, and by the U.S. Environmental Protection Agency under Cooperative Agreement CR 816335-01-0 and the Junta Nacional de Investigación Científica e Tecnológica de Portugal.

APPENDIX

List of Variables

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>coefficients of the aliasing filter</td>
</tr>
<tr>
<td>b</td>
<td>coefficients of the postprocessing filter</td>
</tr>
<tr>
<td>$c_p$</td>
<td>specific heat of water vapor at constant pressure</td>
</tr>
<tr>
<td>$D$</td>
<td>distance to ocean boundaries</td>
</tr>
<tr>
<td>$E$</td>
<td>evapotranspiration</td>
</tr>
<tr>
<td>$f$</td>
<td>Coriolis parameter</td>
</tr>
<tr>
<td>$g$</td>
<td>gravitational acceleration</td>
</tr>
<tr>
<td>$H$</td>
<td>vertical length scale of heating</td>
</tr>
<tr>
<td>$h_M$</td>
<td>moist static energy</td>
</tr>
<tr>
<td>$I$</td>
<td>local slope</td>
</tr>
<tr>
<td>$K_1$</td>
<td>rainfall partitioning coefficient</td>
</tr>
<tr>
<td>$K_2$</td>
<td>snowfall partitioning coefficient</td>
</tr>
<tr>
<td>$L$</td>
<td>latent heat of vaporization</td>
</tr>
<tr>
<td>$L_w$</td>
<td>length of influence of sea-breeze phenomena</td>
</tr>
<tr>
<td>$N$</td>
<td>Brunt–Väisälä frequency</td>
</tr>
<tr>
<td>$p$</td>
<td>precipitation distribution</td>
</tr>
<tr>
<td>$P$</td>
<td>land surface precipitation</td>
</tr>
<tr>
<td>$q_l$</td>
<td>ice-phase water content</td>
</tr>
<tr>
<td>$q_l$</td>
<td>liquid water content</td>
</tr>
<tr>
<td>$q_p$</td>
<td>precipitable water content</td>
</tr>
<tr>
<td>$q_s$</td>
<td>saturated water content</td>
</tr>
<tr>
<td>$q_s^*$</td>
<td>modified saturated water content</td>
</tr>
<tr>
<td>$q_v$</td>
<td>water vapor content</td>
</tr>
<tr>
<td>$Q$</td>
<td>total water content</td>
</tr>
<tr>
<td>$R$</td>
<td>streamflow</td>
</tr>
<tr>
<td>$S(p)$</td>
<td>total removal of $h_M$ by precipitation</td>
</tr>
<tr>
<td>$T$</td>
<td>temperature</td>
</tr>
<tr>
<td>$T_D$</td>
<td>dewpoint temperature</td>
</tr>
<tr>
<td>$x_{\text{min}}$</td>
<td>minimum observed precipitation at a precipitation gauge</td>
</tr>
<tr>
<td>$x$</td>
<td>instantaneous model result at a precipitation gauge</td>
</tr>
<tr>
<td>$x_L$</td>
<td>correlation length</td>
</tr>
<tr>
<td>$Y$</td>
<td>estimated variable</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>interpolation coefficient in the objective analysis scheme</td>
</tr>
<tr>
<td>$\beta$</td>
<td>orographic enhancement function</td>
</tr>
<tr>
<td>$\chi$</td>
<td>observed variable</td>
</tr>
<tr>
<td>$\eta$</td>
<td>correction coefficient of $q_l$</td>
</tr>
<tr>
<td>$\rho(x, y)$</td>
<td>spatial correlation for estimation of surface wind field</td>
</tr>
<tr>
<td>$\rho'(x, y)$</td>
<td>spatial correlation coefficient for estimation of precipitation on days with easterly winds</td>
</tr>
<tr>
<td>$\omega$</td>
<td>weighting factor</td>
</tr>
<tr>
<td>$\omega_d$</td>
<td>frequency of radiative heating and cooling</td>
</tr>
<tr>
<td>$\mu_x$</td>
<td>mean observed precipitation at a precipitation gauge</td>
</tr>
<tr>
<td>$\xi$</td>
<td>subscript that refers to conservative transport</td>
</tr>
</tbody>
</table>

REFERENCES


