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Development of Mountain Climate Generator and Snowpack Model for Erosion Predictions in the Western United States Using WEPP, Progress Report No. 2

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Development of Mountain Climate Generator and Snowpack Model for Erosion Predictions in the Western United States using WEPP

Progress Report No. 2
July 1 – September 30, 1990
Cooperative Agreement No. INT-90530-RJVA
U.S. Forest Service–Utah State University

Utah Water Research Laboratory
Development of Mountain Climate Generator and Snowpack Model for Erosion Predictions in the Western United States using WEPP

Progress Report No. 2
July 1 – September 30, 1990

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Forestry Service Laboratory
Intermountain Research Station
U.S. Department of Agriculture
Forest Service
1221 South Main Street
Moscow, Idaho 83843

November 12, 1990

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EXECUTIVE SUMMARY

This report summarizes work conducted during the funding period (July 1 through September 30, 1990) of a Cooperative Agreement between the United States Forest Service (USFS) and the Utah Water Research Laboratory (UWRL), Utah State University. The purpose of the agreement is to develop a Western Mountain Climate Generator (MCLIGEN) similar in function to the existing Climate Generator (CLIGEN), which is part of the Water Erosion Prediction Project (WEPP) procedure. Also, we are developing a Western U.S. snowpack simulation model for inclusion in WEPP.

In the Western U.S., few meteorological observations exist in high elevation areas where Forest Service properties are located. Therefore, a procedure for estimating climatological variables in mountainous areas is needed to apply WEPP in these regions. A physically-based approach, using an expanded and improved orographic precipitation model, is being utilized. It will use radiosonde data and also lightning data to simulate convective storms. Climatological sequences thus estimated at ungaged locations will be represented using stochastic models, similar to the approach used in the existing CLIGEN, and their parameters will be available to users through maps. By using these stochastic models, WEPP users can synthesize climate sequences for input to WEPP.

During the reporting period we have implemented the Rhea orographic precipitation model and begun preliminary model testing in two regions. Also, we have begun formulation of model modifications for handling convective events. Various snowpack and meteorological data sets have been acquired and others have been ordered. Some of these have been applied in initial applications of several snowpack models which have been recoded in a modular form. Work has commenced on the statistical analysis of western climate sequences, including the preliminary assessment of the alternative stochastic model structures. Additional review of literature has been commenced for establishing design storms and design hydrographs for events of various return periods in mountainous regions.

Accomplishments are summarized in three parts: 1) climatological process models, 2) snowpack simulation models, and 3) stochastic models of climatological variables and parameter regionalization. A chapter of the report is devoted to each of these three parts.
CHAPTER 1
Introduction

1.1 Objective

The overall objective of the work that UWRL is conducting under a cooperative agreement with the USFS is to develop a procedure for generating MCLIGEN as part of the WEPP procedure. As a secondary objective we are also developing a Western U.S. snowpack simulation model for inclusion in WEPP.

This work is part of a large USFS research and development effort and, as such, must provide a usable product within the project schedules established by the USFS. The MCLIGEN which will be developed by UWRL will furnish climate inputs to WEPP with the goal that acceptably accurate erosion predictions are provided for design and planning purposes. Existing procedures for nonorographic areas in CLIGEN are being evaluated and may be modified if necessary to achieve acceptable levels of accuracy. The representation of climate in mountainous areas will be a major challenge because climatological data are scarce and meaningful interpolation of climate variables is more difficult in orographic areas. The project will identify existing techniques which provide adequate climate inputs, adapt existing procedures where appropriate, and develop new procedures within the constraints of available existing data and project resources.

1.2 User Requirements

The MCLIGEN should be capable of providing three climate “event types” as input to WEPP:

- **Initial snowpack water equivalent on a specified date.**
- **Melt period climate** – precipitation, temperature, and solar radiation characteristics.
- **Winter and summer storms** – duration, intensity, and amount.

The WEPP user will need these “event types” accessible in three “event forms”:

- **Design events** associated with various occurrence frequencies or return periods.
- **Continuous simulation** of climate for up to 20 year periods using stochastic methods. This will be particularly useful in assessing the erosion potential from timber harvest areas, and it could include the capability for estimating a probability distribution of erosion potential, average potentials, or perhaps high or low extreme climate cases. High cases could be useful for design of sediment control measures, such as detention basins.
- Selected **representative historical events or sequences** (e.g., average, dry, and wet). This capability would enable users to make erosion estimates for climate sequences based upon historical events (appropriately adjusted when transferred from one location to another), and it would be an alternative to the sequences generated using stochastic methods. The user could select a recorded event or sequence of data from a station or stations which the user considers best represents the conditions at the site which is under evaluation. This type of climate input would also be useful when a user desires to simulate past events as opposed to hypothetical future events.
Users will choose the form of climate input which they use. The generator will have the capability of providing climate inputs based on locational information (such as latitude, longitude, elevation, slope, and aspect).

1.3 Project Status

Three developmental phases were defined in the work plan submitted to the USFS on September 8, 1989:

Phase I: Climate data evaluation and generator design

Phase II: MCLIGEN coding and evaluation at representative sites

Phase III: Generalization to entire Western U.S.

Work undertaken during the second funding period, beginning July 1, 1990, and ending September 30, 1990, has been part of Phase I. Specifically, we have implemented the Rhea orographic precipitation model and begun preliminary model testing in two regions. Also, we have begun formulation of model modifications for handling convective events. Various snowpack and meteorological data sets have been acquired and others have been ordered. Some of these have been applied in initial applications of several snowpack models which have been recoded in a modular form. Work has commenced on the statistical analysis of western climate sequences, including the preliminary assessment of the alternative stochastic model structures. Additional review of literature has been commenced for establishing design storms and design hydrographs for events of various return periods in mountainous regions.

Three UWRL team members participated in the WEPP Core Team Working Group Meeting in Denver during September 1990. A presentation of our approach to the development of both MCLIGEN and the snowpack modeling was given by Drs. Bowles and Bingham. The presentation also included some preliminary results from the orographic precipitation model, two snowpack models, and the climate data analyses.

An abstract for a paper has been submitted to the Western Snow Conference describing a comparison of alternative snowpack simulation models for use in erosion prediction. We propose to submit or prepare other papers on our work so that our research results can be exposed to on-going peer review. Copies of abstracts and papers will be forwarded to Dr. Ed Burroughs of the USFS.

1.4 Outline of Report

The report is divided into four chapters and an Executive Summary. Chapters 2, 3, and 4 address the three major parts of work: climatological process models, snowpack simulation model, and stochastic models and parameter regionalization. Each chapter includes a literature review, discussion of the proposed methodology, and description of work plan. Appendix A contains a literature review of several topics related to the third part of the work, and Appendix B contains a summary of data collected or requested for the snowpack model development. Additional meteorological data were listed in Appendix B of Progress Report No. 1 (Bowles, et al., 1990).
2.1 Objective

The following objective was established for the current reporting period:

To implement an orographic precipitation model on two areas, select some well gaged areas for detailed model development and testing, and formulate modifications for handling convective events.

2.2 Tasks

The following tasks were established for the current reporting period:

Task I-1: Acquire digital terrain map for State of Utah

Task I-2: Implement orographic precipitation model for Utah and select two 50 km x 50 km areas for evaluation of model predictions against SNOTEL, NOAA, USFS and other climate data.

Task I-3: Select well gaged watersheds with high resolution climate data for use in model development and testing.

Task I-4: Formulate modifications to orographic precipitation model to include summer/convective storms and participate in organization of Orographic Precipitation Model User's Group (OPMUG).

2.3 Accomplishments and Problems

2.3.1 Orographic Model Development

During the reporting period, we have installed the Rhea orographic precipitation model on a 386 computer. A Utah terrain data base has been developed and used with the model. Radiosonde data sets that are appropriate for Utah have been collected and formatted for use with the model. We are now in the process of verifying the code and calibrating it to Utah conditions. Our next step will be to modify the code to provide outputs of the dew points, temperatures, and cloudiness that are calculated by the model. While the model is conceptually simple, it contains some subtle nuances which are being studied. The model, for instance, has a built-in easterly wind bias. This bias occurs because of the way in which the Earth's curvature is calculated by the model. It has caused some inaccuracy in fitting the model to the Utah data. Figure 2-1 shows the Utah terrain data, at 1000 feet contours for the Northern Utah Region. Figure 2-2 shows the precipitation pattern calculated by the model for a frontal storm which occurred on April 1, 1984. Comparisons of the predicted and measured precipitation are now being made.
Figure 2-1. 1000 foot elevation contours from terrain grid.
Figure 2–2. Utah precipitation contour plot with wind at 230.
2.3.2. Model Verification Site Identification

We have chosen two sites in Utah for initial model verification and application studies. The two 50 x 50 Km areas will be used to study the model dynamics, calibration and character. The highest concentration of high altitude weather stations in Utah (i.e., the SNOTEL network) is the northern Wasatch, east of Salt Lake City, and in the Uinta mountains. These two areas are very close together, but were selected for the comparison because of their distinctly different precipitation regimes. The Wasatch range runs north and south and receives much of its moisture from orographically augmented frontal storms embedded in west-to-east moving zonal flow. The areas chosen for the study and the higher altitude weather stations in the region are shown in Figures 2-3 and 2-4, respectively.

The Uinta Mountains are located in the rain shadow of the Wasatch and receive a major portion of their moisture from more southerly flow regimes. Winter precipitation occurs mainly when a deep dip occurs in the jet, curving back to the north over southern California. When cyclonic disturbances imbedded in the jet entrain moisture from the Gulf of California, significant snow and rain occurs in the Desert Southwest and in the Uinta Mountains.

The Uintas also have a significant summer precipitation component and will make an ideal location to verify the convective module, to be added to the model. Summer precipitation occurs under two conditions. The first, and most prevalent, is when the Bermuda High moves close to the Florida coasts during mid- and late summer. This high pressure circulation moves high level moisture from the Gulf of Mexico northwest across New Mexico and Utah, eventually flowing up the slopes of the Uintas resulting in summer afternoon showers.

The second summer precipitation mode in the Uintas, and the one producing the largest precipitation events, occurs while the high is in position, and a hurricane moves up the western coast of Mexico. These hurricanes move from the easterly flow regime into the zonal westerlies about 20 degrees north (i.e., mid-Gulf of California). The moisture collected in these storms can be caught in the northwesterly flow and ends up over the Uintas. These periods are typically associated with high instability indices and result in strong summer precipitation events. The summer maximum probable precipitation event is associated with this flow regime (see HMR 49). These Uinta summer precipitation modes and the close spacing of the SNOTEL network in this region were the reason for the selection of this area for model testing.

2.3.3. Convective Storm Model Development

Initial concept development of the convective vertical lift augmentation module for the orographic precipitation model has been completed. Work on the convective storm addition is currently in the literature review process. The model will be used to increase the vertical motion generated by the orographic code during high sun periods. The routines and data being sought will allow us to parameterize the convective cell probability as a function of radiative heat loading, and instability index.

The NWS currently issues shower probability forecasts that are based on the lifting instability index. Since we calculate a vertical profile at each model node, we can use this or a similar routine to provide the probability of convective cell formation. The data used to develop these routines, along with the actual routines used are being collected from the NOAA/NWS technical literature, the NWS Severe Storm Center, and the NWS Numerical Modeling Center. A second data set, the precipitation index, associated with each probability, is also being collected.
Figure 2-3. Northern Wasatch study area.
Figure 2-4. Uinta Mountain study area.
2.3.4. **Orographic Precipitation Model Users Group**

Several investigators are currently using orographic precipitation models in their research in the mountain west. In some cases these are being modified for specific applications. As they work with these models, their combined experience should be useful. We have prepared a list of these investigators and are planning to invite them to attend a meeting to organize an Orographic Precipitation Model User Group (OPMUG). We are attempting to hold this meeting later this fall or early 1991. We had explored coordinating OPMUG with an existing ASCE Task Committee, but concluded that this would not work since the committee will soon complete its state–of–the–art report and then will be disbanded. After the initial meeting, we plan to explore linking OPMUG to a major professional society, such as AMS or AGU so that OPMUG meetings can be held in conjunction with meetings of the selected professional society.

2.4 **Work Plan for October 15, 1990 – March 31, 1991**

The following objective has been established for the next reporting period:

To expand the MCLIGEN model to include the Western United States and to refine the model to generate valid climate parameters in 50 x 50 km application areas. Development of cloud parameters and radiation values will be necessary for generation of necessary climatic parameters.

The following tasks have been formulated for the next reporting period:

1. Obtain and make operable the terrain grid and radiosonde data base for the Western U. S.

2. Develop and run a gridding routine for the radiosonde and terrain data over a portion of the Western United States to establish MCLIGEN model boundary conditions that can be used on a 50 x 50 km scale in application areas.

3. Using atmospheric radiation theory, develop and code a model that when combined with the orographic precipitation model will model development of cloud–type, height, and extent. Concepts from the Hay and Hanson (1978) model, the Tarpley (1979) model, and the Walters (1987) models will be used where applicable.

4. Test the model using a radiation data set collected from a 26 station network for a 550 x 160 km section of Utah that includes both 50 x 50 km application areas.

5. Calibrate the winter and spring data from two 50 x 50 km application areas. Evaluate differences between generated and observed climatic data series to establish: a) whether corrections for local effects are indicated, b) what is the nature of these corrections, c) do differences stem from an inability of the precipitation model to adequately reproduce the physical process, and d) can and should process definitions be changed in the physical model to more faithfully reproduce observed behavior?

6. Continue literature review and evaluate other summer, convective storm information for inclusion in the model. Evaluate the Regional Atmospheric Modeling System (RAMS) routine that handles mature mesoscale convective complexes (MCCs) to determine if it is transferrable. Begin coding of the summer, convective portion of the model.

7. The initial meeting of the Orographic Precipitation Modeling Users Group (OPMUG) will be held in Salt Lake City in late 1990 or early 1991.
CHAPTER 3
Snowpack Modeling

3.1 Objective

The following objective was established for the current reporting period:

To implement several existing snowmelt models, identify well gaged areas for detailed model development and testing, and formulate plans for additional data collection.

3.2 Tasks

The following tasks were established for the current reporting period:

Task II-1: Acquire and implement several existing snowmelt models.

Task II-2: Identify field sites where the data necessary for testing and validation are available, and acquire data. (See Task I-3).

Task II-3: Formulate, with the USFS, plans for development of additional field sites to fill gaps in information provided by existing sites.

3.3 Accomplishments and Problems

This phase of the work has focused on model implementation and data acquisition.

3.3.1 Model Implementation

USU Model. The USU snowmelt model (Riley et al., 1966) has been completely recoded to conform to modern modular programming standards and consistent units. All constants and parameters are read from data files (as opposed to being embedded in the code) so any consistent set of units (such as SI) can be used. The constants, parameters, and variables used are listed in Table 3-1. Figure 3-1 gives preliminary results comparing predicted and observed snowpack depth and water equivalent for Central Sierra Snow Laboratory data. Only the melt factor was adjusted to get this fit. All other parameters were left at initial values taken from various published sources.

While implementing the model the following shortcomings were identified:

- Heat/cold content of the top 1/6th of the snowpack is neglected when air temperature dips below freezing.

- Refreezing of meltwater when the air temperature dips below freezing was not implemented. Various model descriptions offer different approaches, none of which look that appealing.

- Radiation energy inputs are parameterized by temperature, implying no energy input when air temperature is below a threshold, even if the snow is colder and the sun is shining.

Test cases can be contrived to highlight these deficiencies, but the goodness-of-fit in practice indicates that they are not critical at a daily time-scale. Nevertheless, many of the deficiencies can be easily rectified.
Table 3-1. USU model variables.

<table>
<thead>
<tr>
<th>State Variables</th>
<th>Definition</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>T2</td>
<td>temperature at 2/3 depth of the snowpack</td>
<td>°C</td>
</tr>
<tr>
<td>T3</td>
<td>temperature at 1/3 depth of the snowpack</td>
<td>°C</td>
</tr>
<tr>
<td>W</td>
<td>Water equivalent of frozen part of snowpack</td>
<td>m</td>
</tr>
<tr>
<td>D</td>
<td>Snowpack depth</td>
<td>m</td>
</tr>
<tr>
<td>A</td>
<td>Albedo</td>
<td>—</td>
</tr>
<tr>
<td>F</td>
<td>Free water content</td>
<td>m</td>
</tr>
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<tr>
<th>Constants</th>
<th>Definition</th>
<th>Units</th>
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<tbody>
<tr>
<td>Lf = 79.7</td>
<td>Latent heat of freezing</td>
<td>cal/g</td>
</tr>
<tr>
<td>Cw = 1</td>
<td>Heat capacity of water</td>
<td>cal/g/K</td>
</tr>
<tr>
<td>Cs = .5</td>
<td>Heat capacity of snow</td>
<td>cal/g/K</td>
</tr>
</tbody>
</table>

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<th>Parameters</th>
<th>Definition</th>
<th>Units</th>
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<tr>
<td>Km</td>
<td>Melt factor</td>
<td>m/°C/hr</td>
</tr>
<tr>
<td>Ks</td>
<td>Settlement time constant for snowpack</td>
<td>hr⁻¹</td>
</tr>
<tr>
<td>Tm</td>
<td>Temperature index parameter</td>
<td>°C</td>
</tr>
<tr>
<td>Tr</td>
<td>Temperature above which all is rain</td>
<td>°C</td>
</tr>
<tr>
<td>Ts</td>
<td>Temperature below with all is snow</td>
<td>°C</td>
</tr>
<tr>
<td>Tb</td>
<td>Temperature of freezing</td>
<td>°C</td>
</tr>
<tr>
<td>Ka</td>
<td>Albedo decay time constant</td>
<td>hr⁻¹</td>
</tr>
<tr>
<td>Cv</td>
<td>Heat conductivity of coefficient</td>
<td>m²/hr</td>
</tr>
<tr>
<td>Cri</td>
<td>Density of new snow parameter</td>
<td>(°C)²</td>
</tr>
<tr>
<td>Tri</td>
<td>Ref temperature for density of new snow</td>
<td>°C</td>
</tr>
<tr>
<td>Rm</td>
<td>Maximum snow density</td>
<td>—</td>
</tr>
<tr>
<td>Roimin</td>
<td>Minimum initial snow density</td>
<td>—</td>
</tr>
<tr>
<td>Lef</td>
<td>Constant in liquid water holding function</td>
<td>—</td>
</tr>
<tr>
<td>Leg</td>
<td>Gradient in liquid water holding function</td>
<td>—</td>
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<table>
<thead>
<tr>
<th>Site Variables</th>
<th>Definition</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kt</td>
<td>Vegetation transmission coefficient</td>
<td>—</td>
</tr>
<tr>
<td>Slope</td>
<td></td>
<td>°</td>
</tr>
<tr>
<td>Azimuth</td>
<td></td>
<td>°</td>
</tr>
<tr>
<td>Lat</td>
<td></td>
<td>°</td>
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<table>
<thead>
<tr>
<th>Input Variables</th>
<th>Definition</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precip</td>
<td>Precipitation</td>
<td>m⁻¹</td>
</tr>
<tr>
<td>ta</td>
<td>Air temperature</td>
<td>°C</td>
</tr>
<tr>
<td>dt</td>
<td>Time step</td>
<td>hr</td>
</tr>
<tr>
<td>day</td>
<td></td>
<td></td>
</tr>
<tr>
<td>month</td>
<td></td>
<td></td>
</tr>
<tr>
<td>year</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 3-1. Preliminary comparison of USU model and CSSL snow data.
We plan to address this issue in the next reporting period because we believe the deficiencies may be critical for simulating the transient characteristics of snowmelt runoff which is important for erosion.

**SHE Approach.** The SHE snowmelt model (Morris, 1982) has been coded using two methods:

1. The degree-day.
2. The energy budget.

The constants, parameters, and variables used are given in Table 3-2.

These two methods have been compared using data obtained from the Central Sierra Snow Laboratory. Figure 3-2 shows a comparison of predicted and observed snowpack depth and water equivalent. The snowmelt factor for the degree-day method has been adjusted to fit the data.

The SHE model contains several assumptions.

1. Vertical variation in snowpack parameters are neglected and instead each parameter is assumed to be uniform through depth.
2. Heat gained from the ground is assumed to be constant \((2 \text{ J/m}^2/\text{s})\).
3. The snow surface temperature is assumed to be the average snowpack temperature. This may be one important source of error in the model.
4. No snow settling due to aging is allowed.

**PRMS Model.** We have acquired the PRMS model (Leavesley, 1973), but so far we have not isolated the snowpack model components. This is due to a complicated program structure and segmentation required for the PC implementation. However, all the steps necessary to program the model have been reviewed, and the flow chart along with the necessary equations were abstracted from the literature. We plan to get a modular version of the PRMS model working during the next reporting period.

**3.3.2 Data Acquisition and Gaps**

Table 3-3 lists the data sets we either currently have or have ordered. Table 3-4 gives the settings from which each data set was obtained. From these tables note that the gaps in our data are in the Pacific Northwest Region and intermediate canopy densities. The only really detailed data set that has measured melt rates is that from the Central Sierra Snow Laboratory. Meltwater delivery rates at short time intervals (say hourly) are critical to runoff generation and erosion prediction so there is a need to find more data like this.

The data we have are sufficient to continue model development and testing at present. However, to properly evaluate the models, we need more sites where melt runoff is collected at short (hourly) time intervals in different forest settings.

This winter we are collaborating on some research and data collection at Beaver Mountain (near Logan, UT) where temperatures within the snowpack and runoff will be collected in a forest setting or on a mountain top. We hope to, perhaps, expand this to other sites in the future, depending on funding support.
Table 3-2. SHE model variables.

### 1–The Degree Day Method

<table>
<thead>
<tr>
<th>State Variables</th>
<th>Definition</th>
<th>Units</th>
</tr>
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<tbody>
<tr>
<td>SWE</td>
<td>Snowpack water equivalent</td>
<td>m</td>
</tr>
<tr>
<td>TS</td>
<td>Snowpack temperature</td>
<td>°C</td>
</tr>
<tr>
<td>SD</td>
<td>Snowpack depth</td>
<td>m</td>
</tr>
</tbody>
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<thead>
<tr>
<th>Constants</th>
<th>Definition</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>DW = 1000</td>
<td>Density of water</td>
<td>kg/m³</td>
</tr>
<tr>
<td>LHW = 333624.2</td>
<td>Latent heat of fusion</td>
<td>J/kg</td>
</tr>
<tr>
<td>TB = 0</td>
<td>Basic air temperature</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Definition</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>K</td>
<td>Melting factor mm snow</td>
<td>s/°C</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Input Variables</th>
<th>Definition</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>PPT</td>
<td>Depth of precipitation</td>
<td>mm</td>
</tr>
<tr>
<td>TMAX</td>
<td>Maximum air temperature</td>
<td>°C</td>
</tr>
<tr>
<td>TMIN</td>
<td>Minimum air temperature</td>
<td>°C</td>
</tr>
</tbody>
</table>

### 2–Energy Budget

<table>
<thead>
<tr>
<th>State Variables</th>
<th>Definition</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>SWE</td>
<td>Snowpack water equivalent</td>
<td>m</td>
</tr>
<tr>
<td>TS</td>
<td>Snowpack temperature</td>
<td>°C</td>
</tr>
<tr>
<td>SD</td>
<td>Snowpack depth</td>
<td>m</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Constants</th>
<th>Definition</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPW = 238.89</td>
<td>Specific heat of water at constant pressure</td>
<td>J/kg/°C</td>
</tr>
<tr>
<td>CPI = 119.445</td>
<td>Specific heat of ice at constant pressure</td>
<td>J/kg/°C</td>
</tr>
<tr>
<td>CPA = 57.334</td>
<td>Specific heat of air at constant pressure</td>
<td>J/kg/°C</td>
</tr>
<tr>
<td>ZB = 0</td>
<td>Instrument height above the ground surface</td>
<td>m</td>
</tr>
<tr>
<td>ZO = 0.0002</td>
<td>Aerodynamic roughness of snow surface</td>
<td>m</td>
</tr>
<tr>
<td>D = 0</td>
<td>Zero plane displacement</td>
<td>m</td>
</tr>
<tr>
<td>RHOWA = 1</td>
<td>Air density</td>
<td>kg/m³</td>
</tr>
<tr>
<td>Rhow = 1000</td>
<td>Water density</td>
<td>kg/m³</td>
</tr>
<tr>
<td>LHW = 333624.2</td>
<td>Latent heat of fusion</td>
<td>J/kg</td>
</tr>
<tr>
<td>LVW =</td>
<td>Latent heat of vaporization</td>
<td>J/kg</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Definition</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>DN</td>
<td>Turbulent transfer coefficient</td>
<td>°C⁻¹</td>
</tr>
<tr>
<td>QS</td>
<td>Specific humidity of snow surface</td>
<td></td>
</tr>
<tr>
<td>QA</td>
<td>Specific humidity of the air</td>
<td></td>
</tr>
<tr>
<td>RHOWS</td>
<td>Snow density</td>
<td>kg/m³</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Input Variables</th>
<th>Definition</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>PPT</td>
<td>Depth of precipitation</td>
<td>mm</td>
</tr>
<tr>
<td>TMAX</td>
<td>Maximum air temperature</td>
<td>°C</td>
</tr>
<tr>
<td>TMIN</td>
<td>Minimum air temperature</td>
<td>°C</td>
</tr>
<tr>
<td>WS</td>
<td>Wind speed</td>
<td>m/s</td>
</tr>
<tr>
<td>RN</td>
<td>Net radiation</td>
<td>J/kg</td>
</tr>
</tbody>
</table>
Figure 3-2. Preliminary comparison of SHE model and CSSL snow data.
### Table 3-3. Snow data sets.

<table>
<thead>
<tr>
<th>Data Sets</th>
<th>Description</th>
<th>Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Central Sierra Snow Laboratory (85/86 winter).</td>
<td>Detailed meteorology, snowpack, and snowmelt data at forested and open sites.</td>
<td>Have</td>
</tr>
<tr>
<td>2. Lick Creek MT (88/89 and 89/90 winters).</td>
<td>Montana State University thesis, with depth, water equivalent, and snow density measured at two week intervals in sites with four different canopy cover densities. Adjacent SNOTEL station data.</td>
<td>Have</td>
</tr>
<tr>
<td>3. USU data (88/89 winter).</td>
<td>Depth and density measurements at five sites in Tony Grove watershed. Temperatures regressed from Logan, Mount Logan, and Beaver Mountain, nearby SNOTEL and meteorology stations.</td>
<td>Have</td>
</tr>
<tr>
<td>4. Beaver Mountain, CO (1964–1966).</td>
<td>PRMS input and output; however, snowpack measurements to verify against not located yet, may be lost in history and of low value.</td>
<td>Have</td>
</tr>
<tr>
<td>5. Canadian weather and snow survey data.</td>
<td>Canadian data equivalent to SNOTEL and meteorology data requested for about 30 stations in West Canada. Several have radiation or sunshine measurements and snowpack depth measurements. None have snowmelt rates measured. Need information on settings.</td>
<td>Have</td>
</tr>
<tr>
<td>6. Glees site (88–present).</td>
<td>Meteorology, SNOTEL, and hill forest and meadow runoff lysimeters. To get this data we would need to work with Karl Zeller at the Rocky Mountain Forest and Range Station. He estimates that he needs three man months to process data into a usable format.</td>
<td>Do Not Have</td>
</tr>
</tbody>
</table>

### Table 3-4. Classification of climate region and canopy density for data sets in Table 3-3.

<table>
<thead>
<tr>
<th>Canopy Density</th>
<th>Pacific NW (WA, OR)</th>
<th>Sierra Nevada (CA)</th>
<th>Northern Rockies (ID, MT, WY, Canada)</th>
<th>Southern Rockies (UT, CO, AZ, NM, NV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 - 10%</td>
<td>1</td>
<td></td>
<td>2, 5</td>
<td>3, 4</td>
</tr>
<tr>
<td>10 - 40%</td>
<td></td>
<td></td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>40 - 70%</td>
<td></td>
<td></td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>70 - 100%</td>
<td>1</td>
<td></td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

Tasks 1 to 3 in Progress Report No. 1 work plan can be regarded as complete for the USU and SHE approaches. We still need to include the PRMS model and other models such as the existing WEPP snowpack model (Young et al., 1990). Some model evaluation has been done and areas for improvement identified. However, we need to more critically evaluate the rate of meltwater delivery to the top of the soil.

For the next six months we expect to work on Tasks 4–7 of the work plan presented in Progress Report No. 1 (Bowles et al., 1990), namely:

- Further model evaluation and revision.
- Identify and acquire additional data.
- Testing with additional data.

Depending on progress with other sections of this project we could even do some testing with orographic model or stochastic model output as input.
CHAPTER 4
Stochastic Modeling and Parameter Regionalization

4.1 Objective

The following objective was established for the current reporting period:

To assess the statistical properties of western climate sequences, test the adequacy of the existing CLIGEN stochastic model on two areas, and evaluate potential alternative nonparametric and point process approaches.

4.2 Tasks

The following tasks were established for the current reporting period:

Task III-1: Assess statistical properties of observed western climate sequences

Task III-2: Test CLIGEN structure on selected areas in Utah

Task III-3: Evaluate alternative CLIGEN structures for Western U.S. conditions using nonparametric and point processes

4.3 Accomplishments and Problems

Two major directions of work, related to Tasks 1 and 5 (Bowles et al., 1990), were pursued in the last quarter. These were: 1) testing of the adequacy of the Markov Chain model used by the current version of CLIGEN with data from Utah (Task III-1 and -2), and 2) the development of an alternative stochastic model for the generation of climatic sequences (Task III-3). The motivation for the latter stems from desires to: (a) address some known deficiencies of the Markov Chain approach for the generation of climatic sequences at a point, and (b) develop a more reasonable framework for consistent space-time generation of climatic sequences in conjunction with the physical model being developed. An overview of the progress made along each of the above directions is presented in the subsequent paragraphs. Details of some of the procedures developed or under consideration are presented in Appendix A.

4.3.1. Characterization of Data/CLIGEN Testing

The purpose of this work is to identify salient characteristics of at-site rainfall and to see how well CLIGEN reproduces these characteristics. Efforts were made to acquire the raw data used by CLIGEN for stations at various elevations in Utah. The data files provided with CLIGEN have statistical summaries of data from selected stations in Utah and the Western United States. The data were unsuitable for developing the kinds of measures we were interested in. A computer program was written to take raw meteorological data and to compute statistics that were felt to be of interest, as well as the statistics currently used by CLIGEN. These statistics include:
1. Average number of wet days per month and per year.

2. Mean, standard deviation, skew, and probability density function (p.d.f.) of dry and wet spells (consecutive dry or wet days) per month.

3. Maximum daily rainfall per month.

4. Mean, standard deviation, skew, and p.d.f. of precipitation depth on rainy days per month.

5. Correlation between precipitation depth and the length of a wet spell.

6. Longest wet and dry spell per month, per year, and over the record.

7. Correlation between precipitation on a day and temperature on the same and next day.

These statistics relate primarily to at-site precipitation at daily or longer time scales. This was the primary climatological variable of interest in our preliminary work, because of its prominence in CLIGEN and the nature of data that were readily available to us. Extensions to this program to investigate disaggregation of rainfall within the daily period and to estimate multivariate (joint) p.d.f.'s of selected variables will be incorporated in due course. In summary, the statistics of interest are computed monthly, seasonally, and annually. Their moments (mean, variance, etc.) are computed and a nonparametric density estimation method (kernel density estimation) is used to infer the unconditional probability density of the statistic of interest. Details of kernel density estimation and a discussion of its utility in recovering the underlying probability density function of discrete or continuous random variables are provided in Appendix A.

We had difficulty obtaining high resolution (sampled more frequently than daily) data. A number of sources (National Weather Summary, Asheville, Reno) for acquiring the data were recommended by Arlen Nicks. These sources were pursued with mixed success. Data that are now available on our computers are listed in Appendix B. The version of CLIGEN we were provided with was also tested. We found a problem with an array index used for the wet/dry probability matrix, and some other results appeared to be inconsistent or unrealistic. Arlen Nicks was helpful in clearing up these problems at the Denver WEPP group meeting. He has graciously agreed to send us a revised version of CLIGEN and a tape with the high resolution (15 min) data set for Utah. We are looking forward to working with these materials as soon as they become available.

Some examples of results from our preliminary investigations into precipitation at the Salt Lake City airport from 1949 to 1989 are provided in Figures 4-1 through 4-10. Figure 4-1 chronologically shows the precipitation depth per wet spell. Figure 4-2 shows it as a frequency histogram, and Figure 4-3 shows its p.d.f. estimated from a fixed bandwidth kernel density estimator (see Appendix A). The apparent multimodality in the tails of the p.d.f. in Figure 4-3 is most likely a consequence of using the fixed bandwidth and may disappear when a variable bandwidth kernel estimator is used. A skewed p.d.f. with a long right tail is suggested. This is consistent with the choice of a lognormal, gamma, or exponential distribution. We have not yet tested how well the distributions fit with this data set. The standard tests (e.g. Chi-square, Kolmogrov–Smirnov) often do not have adequate power to discriminate between distributions in the same family. We are currently developing a method similar to the Kolmogrov–Smirnov test where a likelihood statistic (Kullback–Liebler distance) is estimated between each parametric candidate and an "optimal" kernel density estimate. We will select the parametric p.d.f., with the minimum Kullback–Liebler distance from the kernel density estimate. We expect this test to be more powerful since the "smoothing," or interpolation, between the raw data in the sense of a probability density
Figure 4-1. Precipitation depth per wet spell for SLC (1949-1989).
Figure 4–2. Frequency analysis for precipitation depth per wet spell for SLC (1949–1989).
Figure 4-3. Kernel density function for precipitation depth per wet spell for SLC (1949–1989).
Figure 4–4. Frequency analysis for wet spell length for SLC (1949–1989).
Figure 4-5. Longest wet spell per month for SLC (1949-1989).
Figure 4-6. Longest dry spell per month for SLC (1949-1989).
Figure 4-7. Number of wet days per month for SLC (1949–1989).
Figure 4-8. Number of wet days per year for SLC (1949-1989).
Figure 4-9. Maximum daily precipitation per month for SLC (1949-1989).
Figure 4–10. Average monthly precipitation for rainy days for SLC (1949–1989).
is done more efficiently by the kernel estimator than by the observation classification procedures used in the traditional methods.

A frequency analysis of wet spell length is provided in Figure 4-4. Figures 4-5 and 4-6 present, chronologically, the longest wet and dry spells per month, respectively. Figures 4-7 and 4-8 present the number of wet days per month and per year. Figures 4-9 and 4-10 present the maximum and average daily precipitation (for rainy days) per month for Salt Lake City. Additional analyses to estimate p.d.f's of wet and dry spell lengths were also performed. We are revising these analyses. The use of a discrete kernel is needed in this situation since the dry (or wet) spell length is an integer number of days. A suitable discrete kernel is being investigated.

4.3.2. Development of New Modeling Strategies

Our objective is to develop a stochastic model for synthetic climate generation that is conceptually simple, theoretically consistent, allows the data to determine its structure as far as possible, and accounts for clustering of precipitation events and for other similar features that may be identified from our data analysis. An important key feature is to have a formulation that readily accommodates extension to a space–time model and can incorporate spatial solutions from the physically–bound orographic precipitation model that we are adapting (see Chapter 2).

The orographic model is expected to estimate climate variables at a spatial resolution much higher than the sparse weather station network at high elevations in the Western U.S. and an effective temporal resolution of 12 hours. This temporal resolution is consistent with a stochastic model formulated at a daily time step. Thus, we will have a situation where we will have a sparse, “accurate” (or representative) source of information (i.e., a few real observation sites) and a synthetic (or estimated) higher resolution data set largely derived from surrogate information through an idealized physical model. It is not possible to theorize a priori what the nature of the relationship or the degree of correspondence between the statistical properties of the two data sets should be. It is necessary to modify the results from the orographic model, such that they reproduce an arbitrary number of properties of the observed sequences at each site and that the estimates at ungaged points represent smooth and consistent interpolates of the estimates at the gaged sites. Such a modification can be conceptualized through Bayes theorem if we can develop appropriate estimates of the probability densities of the spatially and temporally distributed climatic variables from the two sources.

One of the attractive features of the Markov Chain formulation of precipitation occurrence is the nonparametric nature of the model. The data are used to directly estimate the daily transition probabilities from one state (e.g., wet) to another (e.g., dry) without a further assumption as to underlying distributional structure (e.g., an exponential distribution). In extensions of Markov Chain formulations to admit clustering and other behavior (e.g., the renewal or point process models), probability distributions (e.g., exponential) are assumed for the length of wet or dry spells. In most traditional models, similar assumptions (e.g., the double exponential) may also be made for the probability distribution of the rainfall amount per event. While such distributions may fit the data reasonably well in some situations and for some data sets, it is rather disquieting to adopt them by fiat. It is our belief that hydrologic models should (a) show (rather than obscure) the interesting features of the data, (b) provide statistically consistent estimators, and (c) be robust. Consistency implies that the estimator converges in probability to the correct estimate. The standard practice of assuming a distribution and then calibrating the model to it clearly obscures features of the data and may not lead to a consistent estimator from site to site. Robustness refers to resistance to outliers in the data. Most traditional methods are calibrated based on least–squares norms and are, consequently, sensitive to outliers. Tests of adequacy of fit, e.g., the
Chi-square test, have low power and generally fail to discriminate between distributions. Notions of independence or dependence between elements of a data set often go unchecked in practice.

There has been remarkable progress in the development of nonparametric estimates of probability densities and regression functions in the last ten years. Such methods consider pointwise estimation of the density or the regression function, through piecewise continuous smoothing functions, without the a priori assumption of an underlying density or regression function. The resulting density may be uni- or multimodal, and issues of clustering or mixing of causative factors are thus naturally accounted for. Some examples of the use of such methods for Markov processes and rainfall runoff modeling are provided by Yakowitz (1985, 1987). We feel that these methods are likely to be a powerful building block for what we have in mind. Accordingly, we reviewed the relevant literature in detail. Some interesting and relevant techniques that pertain to the estimation of multivariate probability density functions in a Markov process context and of covariance structures from unequally spaced data are presented in Appendix A.

The general structure of the at-site precipitation model that we are developing is schematically described below. All probability densities referred to below are estimated using a fixed or variable bandwidth kernel density estimator, as described in Appendix A.

Precipitation Occurrence (Step 1). Consider the nonparametric estimation of the probability density of wet spells and dry spells. A wet spell is defined as the number of consecutive days with measurable precipitation. A dry spell is defined as the number of consecutive days with no measurable precipitation. A wet spell cannot follow a wet spell. A dry spell cannot follow a dry spell. Consider two cases:

a) The probability density function (p.d.f.) of the length of a wet spell is independent of the length of the preceding dry spell. The distributions are \( f(t_w) \) and \( f(t_d) \) for wet spell length \( t_w \) and dry spell length \( t_d \), respectively:

\[
f(t_w) = \frac{1}{nh(t_w)} \sum_{i=1}^{n} K\left( \frac{t_w - t_{w_i}}{h(t_w)} \right) \quad \text{and} \quad f(t_d) = \frac{1}{nh(t_d)} \sum_{i=1}^{n} K\left( \frac{t_d - t_{d_i}}{h(t_d)} \right)
\]

where \( t_{w_i} \) is the length of the \( i \)th wet spell, \( h(\cdot) \) is a bandwidth, \( n \) is the number of wet spells, and \( K(\cdot) \) is a discrete kernel

b) The length of a wet spell and of the preceding dry spell are dependent random variables, and we are interested in the conditional p.d.f. of one given the other. The distributions of interest are \( f(t_w, t_d), f(t_w), f(t_d), f(t_w|t_d) \) and \( f(t_d|t_w) \). Note that the conditional density \( f(t_w|t_d) = f(t_w, t_d)/f(t_d) \):

\[
f(t_w, t_d) = \frac{1}{nh(t_w)h(t_d)} K(t_w, t_d, t_{w_i}, t_{d_i}, h(t_w), h(t_d))
\]
where $t_{wi}$ and $t_{di}$ are the lengths of successive wet and dry spells, $n$ is the number of pairs of wet and dry spells, $h(t_{wi})$ and $h(t_{di})$ are bandwidths for wet and dry spell length, and $K(.)$ is a composite kernel function for $t_{wi}$ and $t_{di}$.

A kernel appropriate for a discrete random variable is used to ensure that an integer number of days can be generated. The number of days representing dry and wet spells are generated alternately from these distributions.

*Wet spell description (Step 2).* Estimate a joint probability distribution $f(n_{wi}, t_{ej}, p_{ej}, p_{ew})$ of the number of precipitation events in a wet spell, the time interval between these events as a function of the length of the wet spell, the event duration, and precipitation depths per event and per wet spell. We are investigating the development of minimum variance kernels for this situation which have not been addressed in the nonparametric density estimation literature. The complicating factors are: 1) a joint density of discrete and continuous random variables is needed; 2) additional conditions (e.g., sum of event interarrival times and event durations have to sum to a discrete length of the total wet spell); and 3) direct data on precipitation per event may or may not be available (i.e., the density of precipitation depth may need to be estimated through a deconvolution process rather than a "known" convolution process).

Thus far, we have decided on the use of product kernels for the joint distribution. These kernels are derived by specifying independent, discrete, or continuous marginal kernels for each random variable, as appropriate. Thus, the kernel bandwidth for each random variable will have to be picked independently.

We expect to use either maximum likelihood cross validation or to develop an equivalent entropy cross validation measure to estimate an equivalent, fixed bandwidth. A strategy to perturb this bandwidth across the sample using nearest neighbor distances and directional considerations is being investigated. Note, once again, that the conditional density of a random variable of interest may be developed as a ratio of the joint density and the unconditional density of the "independent variable." The data requirements for a reasonable estimate of probability density increase dramatically as higher dimensions (more variables) are considered. Consequently, logical breakdowns of the set of variables into smaller groups (e.g., 2) will also be considered.

*Event structure (Step 3).* If high resolution data (15 minutes in time) are available and their use appears appropriate, we will attempt to develop a time distribution of event rainfall conditioned on the wet spell length, the event number, the event duration, and the event precipitation depth. The feasibility of this step, and the computational burden imposed by it, may be prohibitive. However, some efforts along this direction may be pursued.

*Multivariable dependence (Step 4).* Incorporate dependence of precipitation on temperature (or vice versa) and or wind statistics.

Conceptual models for Steps 1 and 2 are currently being developed. We are already estimating the unconditional p.d.f.'s of some of these variables using kernel density estimators. Examples of these estimates for the Salt Lake City data were presented earlier. Work on Steps 3 and 4 has not yet begun.

**4.4 Work Plan for October 15, 1990 – March 31, 1991**

The following objectives have been established for the next reporting period:

1. To continue assessment of statistical properties of western climate and utility of CLIGEN structure in the Western U. S.
2. To formulate MCLIGEN stochastic model structure.

The following tasks have been formulated for the next reporting period:

1. Development of expanded database on western weather.

2. Expanded list of statistics to consider multivariable and multisite statistics and their dependence structures.

3. Development and dramatization of at-site and multisite probability distributions of key variables.

4. Development and testing of a nonparametric point process model:
   a) Model formulation and theoretical properties.
   b) Model performance with synthetic data sets and comparison with the Markov Chain.
   c) Model performance with real data.
APPENDIX A
Stochastic Modeling and Parameter Regionalization—Literature Review
A brief review of some literature relevant to the discussions in the earlier sections is presented in this appendix. A brief introduction to kernel density estimates of p.d.f.'s is first provided. This is followed by a brief review of some models currently used for precipitation modeling. Finally, a review of some recent work using nonparametric density estimators in a renewal/point process context is presented.

A.1. Kernel Density Estimates

A number of nonparametric estimators of the probability density exist. Hydrologists are familiar with the frequency histogram as an estimator of the p.d.f. While the histogram is capable of showing us features of the data, it has several drawbacks. It is difficult to manipulate analytically, and it is not easy to visualize for multivariate situations. The indicated frequency distribution is sensitive to the class width, as well as the origin of each class. Silverman (1986) illustrates these problems graphically. Generalizations of the basic idea of the histogram have been pursued to address these problems. These methods typically consider the probability density function to be derived through a weighted linear combination of the observations. Such an estimate may be defined at an arbitrary point $x$ in terms of the observations $X_i$ as:

$$f_n(x) = \frac{1}{n} \sum_{i=1}^{n} w(X_i, x)$$

(A.1)

where $w(X_i, x)$ is a weight function that is positive, integrates to unity, and assigns most of its weight near $X_i$. Clearly, the resulting density estimate $f_n(x)$ is a density and inherits any smoothness properties that may be built into the weight function $w(X_i, x)$. Examples of such estimators include the kernel density estimator, the nearest neighbor estimator, orthogonal series estimates, and histosplines or log spline density estimates. Lall and Bosworth (1990) present an overview of these methods and show the equivalence of all these methods to the kernel density estimator. Consequently, we shall discuss only the kernel density estimator here. This estimator is also used by Yakowitz (1985), Masry (1983, 1988), Karr (1986), and Phelan (1990).

Tarter and Kronmal (1976) argue that one can improve the histogram by centering blocks at each observation and then using boxes of shapes other than a rectangle. This is precisely what the kernel estimator does. It was introduced by Rosenblatt (1956) and is defined in the general multivariate case as:

$$f_n(x) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{h(x)^d} K \left( \frac{x-X_i}{h(x)} \right)$$

(A.2)

where $K(.)$ is a kernel function placed on the observation $X_i$, $h(x)$ is the width (smoothing parameter) of the kernel evaluated at $x$ (or $X_i$), and $x$ is a $d$-dimensional random variable.

The kernel function is usually required to be a symmetric function, that is, a density ($\int K(t)dt = 1$) with expectation 0 ($\int tK(t)dt = 0$) and finite variance ($\int t^2K(t)dt = \text{constant} < \infty$). Note that $t = (x-X_i)/h(x)$. These properties ensure that if $h(x)$ is properly chosen, such kernels lead to consistent estimators in terms of mean square error (MSE) or mean integrated square error (MISE). However, kernels that do not satisfy these properties are sometimes used. Indeed, Devroye and Gyorfi (1985)
only assume that $K(.)$ is a positive density function in showing it is consistent ($I_{n} \rightarrow \theta$ as $n \rightarrow \infty$) in the $L_1$ norm ($I_{n} = \int |f_n - f|$) for all densities $f$. In terms of asymptotic MSE (large sample sizes, typically greater than 50 or 100), there is apparently little to choose from between different kernel functions. Since the density estimate $f_n$ inherits the smoothness, differentiability, and tail properties of the kernel function $K(.)$, these characteristics, rather than accuracy criterion, dominate kernel selection. Some examples of kernel functions that are used are given in Table A-1. The kernel estimator has finite support if the kernel function has finite support. Extrapolation beyond the range of values in the sample may be possible up to a point if the kernel function has infinite support (e.g., the normal or cauchy kernels). Figure A-1 (Silverman, 1986) provides an excellent illustration of the basic idea in the development of a kernel density estimator using a normal kernel for a univariate situation.

The bandwidth $h(x)$ is the critical parameter in developing a kernel estimator. The bandwidth $h$ has to satisfy $h^{-0}$ as $n \rightarrow \infty$ and $nh^{-8}$ as $n \rightarrow \infty$. Parzen's (1962) work, and that of several other investigators since, focused on fixed kernel estimators ($h(x) = h$) where the bandwidth $h$ is constant. This leads to a single parameter model. Unfortunately, where $h$ is fixed across the sample, the resulting density estimate from a finite sample is either oversmoothed ($h$ large) or noisy in the tails ($h$ small). The choice of $h$ from a sample is usually made by considering an appropriate loss function (e.g., MISE or maximum likelihood) and cross validation, with reference to the optimal value for the kernel used and a parametric density, or through "plug in" methods and smoothness considerations. Estimators where $h(x)$ depends on $x$ or $X_i$ and is not constant over the sample are called variable kernel estimators. Breiman et al. (1977) were perhaps the first to develop an effective strategy for a variable kernel estimator by considering the distances of $k$ nearest neighbors to $X_i$ in prescribing $h(x)$. The bandwidth $h(x)$ is given by $h_{dk}(x)$ where $h$ is a fixed bandwidth, and $d_k(x)$ is the distance to $k$ nearest neighbors from the point $x$. The number of nearest neighbors, $k$, and the bandwidth, $h$, may be chosen by similar objective methods. Bean and Tsokos (1980) provide a more useful modification of the Breiman et al. model. They consider a stabilized jacknifed maximum likelihood cross validation scheme to select $h(x_i)$, and they also consider bandwidths $h(x)$ that depend on nearest neighbors to the point at which $f_n(x)$ is to be evaluated rather than at the data points. We have had success with both Breiman et al.'s and Bean's and Tsokos' methods.

An example of a kernel density estimator using the Normal Kernel and the daily precipitation depth at Salt Lake City is shown in Figure 4-3. A technique called reflection was used to restrict the domain of the resulting p.d.f. to $(0, \infty)$, rather than $(-\infty, \infty)$.

A.2. Temporal Rainfall Models at a Single Site

There are several models which have been suggested in the literature as alternatives to the Markov Chain (MC) model. Some of these are:

1. The wet-dry spell or alternating renewal model.
2. Point-process (PP) models:
   a. Continuous-time PP.
   b. Discrete-time PP.

A.2.1. The Wet-dry Spell Approach

In probabilistic terminology, this approach is also called the alternating renewal model (ARM); the term "renewal" stems from the implied independence between the dry and wet period length while
### Table A-1. Examples of kernel functions.

**Continuous Random Variables, Univariate**

<table>
<thead>
<tr>
<th>Kernel</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rectangular</td>
<td>( K(t) = \frac{1}{2}</td>
</tr>
<tr>
<td>Normal</td>
<td>( K(t) = (2\pi)^{-\frac{1}{2}} e^{-t^2/2} ) infinite support</td>
</tr>
<tr>
<td>Cauchy</td>
<td>( K(t) = 1/((\pi (1 + t^2)) ) moments don't exist; thick tailed, extrapolates tails well</td>
</tr>
<tr>
<td>Epanechnikov</td>
<td>( K(t) = \frac{3}{4\sqrt{5}}(1 - \frac{t^2}{5})</td>
</tr>
<tr>
<td>Sacks</td>
<td>( K(t) = 2.81 - 3.01t - .75t^2 ) theoretically optimal for ((0, \infty))</td>
</tr>
<tr>
<td>Sacks</td>
<td>( K(t) = .96 - 1.2t^2 - .33t^4 ) theoretically optimal for ((-\infty, \infty)) with lower bias than Epanechnikov in tails</td>
</tr>
</tbody>
</table>

**Continuous Random Variables, Multivariate (d dimensions)**

<table>
<thead>
<tr>
<th>Kernel</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>( K(t) = (2\pi)^{-d/2} e^{-|t|^2} ) (-|t|^2) is the Euclidean norm of t</td>
</tr>
<tr>
<td>Epanechnikov</td>
<td>( K(t) = (c_d)^{-1} (1 - |t|^2) ) (c_d = \text{volume of d dimensional sphere})</td>
</tr>
</tbody>
</table>

Multivariate kernels can generally be formed as the product of univariate kernels over d.

**Discrete Random Variables, Univariate**

<table>
<thead>
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<th>Kernel</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hill</td>
<td>( K(t) = 1 ) if (</td>
</tr>
<tr>
<td>Geometric</td>
<td>( K(x) = 0.5(1 - h)h \frac{</td>
</tr>
</tbody>
</table>

Note: \( t = (x - x_i)/h \)
Figure A-1. Kernel estimates showing individual kernels.

Window widths: (a) 0.4; (b) 0.8
the term "alternating" is used to indicate that a wet (dry) is always followed by a dry (wet) period, i.e., no transition to the same state is possible.

Green (1964) developed a wet–dry spell model in which exponential distributions are assumed for the lengths of the dry spell \( f(t) = \alpha e^{-\alpha t} \) and wet spell \( f(t) = \beta e^{-\beta t} \). The model fit the Tel-Aviv data well. Eagleson (1978) considered Poisson arrivals of rectangular intensity pulses that have random depth and duration to represent point precipitation.

Some relationships of interest for an ARM are:

1) the probability of obtaining exactly \( v \) events in a time period \( t \):

\[
P_{\theta | t}(v) = \frac{(\theta t)^v e^{-\theta t}}{v!} \tag{A.3}
\]

where \( \theta = \) average arrival rate of the storm events;

2) probability that a storm will arrive after elapsed time \( t_a = 1 - e^{-\theta t_a} = F_T(t_a) \);  

3) the distribution of interarrival times for a Poisson process is \( f_T(t_a) = \theta e^{-\theta t_a} \) with a

mean \( = \frac{1}{\theta} \) and variance \( = \frac{1}{\theta^2} \); and

4) Total precipitation delivered by \( v \) events is \( p(v) = \sum_{i=1}^{v} h_i \), the total precipitation (depth from single storm).

Small and Morgan (1986) derived a relationship between a continuous time wet–dry spell model with Gamma distributed dry intervals and a Markov Chain (MC) model for daily rainfall.

Disadvantages of the wet–dry spell approach can be listed as follows:

1) It is not easy to define independent events or storms. This problem is more pronounced in hourly data where wet sequences separated by one or several dry hours may still correspond to the same rainfall event (Restrepo-Posada and Eagleson, 1982).

2) The second problem stems from the varying duration of the events which requires that the cumulative rainfall amounts corresponding to each event should be conditioned on the duration of the events. This may pose a problem, especially with short records and for events of extreme duration.

3) Once the total storm has been modeled, it has to be redistributed within the wet period (internal storm characteristics), and this requires additional statistical information to be extracted from the limited data available.

4) It seems that wet spell approach is more appropriate for the study of the external, rather than the fine-scale internal, storm characteristics.

A.2.2. The Point-process Approach:

A point-process (PP) is a stochastic process which describes the occurrence of events in the modeling space. A discrete-time PP permits the events to occur only on the marks specified by equally spaced increments, while the continuous-time PP allows the event to occur anywhere on the time axis.

A poisson process is a stochastic process in which the interarrival time of events is modeled as an exponentially distributed:
and the number of events in a time \( N(A) \) is independent and poisson distributed:

\[
P[N(A) = K] = \frac{e^{-\mu(A)}\mu(A)^K}{K!}
\]  

(A.5)

A Cox process (doubly stochastic poisson process) is a poisson process with the mean measure \( m(A) \) made random:

\[
P[N(A) = K] = \frac{e^{-\mu(A)}\mu(A)^K}{K!}
\]  

(A.6)

A Neyman-Scott is a poisson process with clustering taken into consideration. It emerges as a general point stochastic model for the rainfall point processes that envelopes the models with independent counting increments as its special cases.

Foufoula-Georgiou and Lettenmaier (1987) introduced a Markov renewal (MR) model for the description of daily rainfall occurrences and, by defining an event as a day with measurable precipitation, the model cast into the discrete-time PP framework. In the MR model, the sequence of times between events (defined as any wet day or hour) is formed by sampling from two geometric distributions according to transition probabilities specified by a MC. The MR process is a clustered process and has, as a special case, the MC model. It differs from a MC in that the probability of having rainy days does not depend on the condition (rain, non-rain) of the previous day but on the number of days since the last rain. The amount of precipitation on wet days is described by an exponential p.d.f. Foufoula-Georgiou and Lettenmaier showed that the MR is capable of preserving both the short-term and long-term structure of rainfall.

Foufoula-Georgiou and Lettenmaier (1987) studied continuous-time and discrete-time PP models for rainfall occurrence series; they concluded that, if rainfall occurrences are interpreted as the event of a PP, the continuous-time PP is not directly applicable since it fails to account for the time discreteness of the sample process. In general, the study of rainfall occurrences under continuous-time PP may result in misleading inferences regarding clustering (dispersion) and, consequently, incorrect interpretations of the underlying rainfall generating mechanism.

A.3. Nonparametric Point Processes

Some recent developments, in the probability literature, that use nonparametric density estimators in a point process context are outlined herein.

Masry (1988) presents some results for joint density estimators from random sampling of continuous-parameter stationary processes. He considers \( \{X(t), -\infty < t < \infty\} \) to be a stationary process with a bivariate density function \( f(x_1, x_2; t), t > 0 \), where \( \{t_i\} \) is a renewal point process on \([0, \infty)\), \( x_1 \) is \( X(s) \), and \( x_2 \) is \( X(s + t) \). He develops kernel density estimators \( \hat{f}_n(x_1, x_2; t) \) based on discrete time observations \( \{X(t_j), t_j, j = 1, n\} \). Consistency of the estimates and their central limit behavior is established. This work has direct relevance to what we are interested in. Precipitation may be considered to arise from a point process with observations recorded at discrete intervals (e.g., days or hours). Of interest is
the joint probability distribution of precipitation depth (and/or occurrence) at arbitrary intervals of
time (e.g., one day apart or \( t \) days apart).

Masry considers the sampling instants \( t_j \) to be random. In this context, one may consider a discrete
point process or renewal model for precipitation. Masry (1983) had earlier considered the use
of kernel density estimators for the unconditional density \( f(x) \) (this process is identical to the standard
kernel density estimator described earlier) of the continuous time process \( X(t) \) from discrete time ob-
servations, and he had estimated its bias and covariance, as well as the effect of the sampling scheme
and the sampling rate on the estimate. He also established conditions such that the bias and covarian-
ce of the resulting estimate were identical to those obtained for classical estimators that considered
independent observations. Strong consistency of the kernel density estimator was established for a variety of random and structured sampling schemes and for various mixing assumptions (these essen-
tially describe the rate at which the dependence structure tends to zero as the sampling interval in-
creases). Masry defines the renewal process \( t_j \) as:

\[
t_0 = 0, \quad \text{and} \quad t_j = \sum_{i=1}^{j} T_i
\]

where the interarrival times \( T_i \) are independently and identically distributed random variables with
a common p.d.f. \( p(x) \) on \([0, \infty)\) and \( E[T_i] = 1/\beta \) and is finite.

Masry then considers a positive definite, compact, and symmetric kernel \( K(x_1, x_2) \) for \( x_1, x_2 \), and
\( W(t) \) for \( t \), with bandwidths \( b_n(x) \) and \( b_n(t) \). The estimate of the joint distribution \( f_n(x_1, x_2; t) \) of \( x_1, x_2 \) is then given by:

\[
f_n(x; t) = \frac{1}{np(t)} \sum_{i=1}^{n} W_n(t - T_{i+1})K_n(x - X(t_i)) = \frac{\sum_{i=1}^{n} W_n(t - T_{i+1})K_n(x - X(t_i))}{\sum_{j=1}^{n} W_n(t - T_j)} \quad (A.8)
\]

Note that the above expression is a direct consequence of using marginal product kernels for \( t \)
and \( x \). An arbitrary multivariate kernel is used for \( x \). Extensions to arbitrary, multivariate densities
or dependence structures for \( x \), or \( x \) and \( t \), follow in the same spirit. Some of these issues are discussed
in a forecasting context by Kreiger and Masry (1985).

Diggle (1985) uses the kernel density estimator in a slightly different context to smooth point pro-
cess data. He considers a one-dimensional point process and develops a method for estimating its
local intensity. The local intensity \( \lambda(x) \) refers to the rate function of an inhomogeneous Poisson process.
Such a process is often known as a doubly stochastic Poisson process. Note that the local intensity \( \lambda(x) \) is not observable. Rather, it is inferred from a realization of the underlying point process.

The motivation for Diggle's work stems from the observation that, for a general point process
(which has potentially heterogeneous data), it is difficult to support the hypotheses that the local intensity
is the result of a stationary process. In particular, for clustering phenomena, the clustering of

A-7
points may be mathematically indistinguishable from variations in local intensity of the process. Diggle points out that the linear Cox process has precisely this dual interpretation. Thus, while a general point process model may be theoretically correct and capable of reproducing clustering, identification of clustering processes from data and correct parameterization of the model may be difficult. This observation is clearly important where parametric point process models, e.g., Cox or Neyman-Scott, are considered for use with precipitation data. Masry’s approach, which explicitly considers local densities through the kernel density estimator, is not compromised by Diggle’s observation. Diggle’s estimator of the local intensity of the point process is similar to Masry’s (1983) estimator of the unconditional p.d.f. of x, except that he considers the point process x to have compact support [0,T], thus necessitating an “end correction” or normalization in probability:

\[ \lambda(x) = \sum_{i=1}^{n} \frac{-1}{nb_n} K\left(\frac{x-x_i}{b_n}\right) \]

\[ = \frac{1}{T} \int_{0}^{T} \frac{1}{b_n} K\left(\frac{x-u}{b_n}\right) d\mu \]

where \( K(\cdot) \) is a kernel function and \( b_n \) is a bandwidth.
APPENDIX B
Data Available
1-Central Sierra Snow Laboratory (1985/1986 Winter)

a - Open Site
   Hourly open infrared snow surface temperature (°C)
   Open elevated wind speed (m/s)
   Open elevated wind direction (degree)
   Precipitation increment for the hour (in)
   Open elevated air temperature (°C)
   Open elevated dewpoint (°C)
   Open elevated relative humidity (%)
   Open elevated long-wave radiation (ly/min)
   Open elevated incident short-wave radiation (ly/min)
   Open ground net short radiation (ly/min)

b - Forest Site
   Forest air temperature (°C)
   Forest dewpoint temperature (°C)
   Forest relative humidity (%)
   Forest ground wind speed (m/s)
   Forest wind direction (degree)
   Forest net radiation (ly/min)

   Average air temperature
   Average soil temperature
   Total rainfall per day
   Minimum and maximum relative humidity
   Wind speed
   Wind direction
   Solar radiation (ly/day)
   Snowpillow (1982 – 1989) from a nearby SNOTEL station ATWOOD LAKE (10J45S)

   Monthly precipitation (1965–1989)
   Snowpillow
   Maximum air temperature
   Minimum air temperature
   Precipitation

   Daily solar radiation
   Maximum air temperature
   Minimum air temperature
   Maximum relative humidity
   Minimum relative humidity
   Precipitation
   Penman evaporation
5—Silver Lake, Utah (July, 1948 – May, 1989)
   Daily precipitation
   Maximum temperature
   Minimum temperature
   Snowfall

6—Salt Lake City, Utah (July, 1948 – May, 1989)
   Hourly precipitation
   Daily precipitation
   Maximum temperature
   Minimum temperature

7—Canadian weather and snow survey data
   These data have been delivered, but we have not yet read them off the magnetic tape. Table B–1 lists the sites requested, and Table B–2 lists the data elements requested. Not all the data is available at each site.
Table B-1. Canadian data sites.

<table>
<thead>
<tr>
<th>Station No.</th>
<th>Station Name</th>
<th>Starting Date</th>
<th>Ending Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>1100014</td>
<td>Abbotsford A</td>
<td>1963 11</td>
<td>1976 11</td>
</tr>
<tr>
<td>1160899</td>
<td>Blue River</td>
<td>1970 11</td>
<td>1980 06</td>
</tr>
<tr>
<td>1091169</td>
<td>Burns Lake</td>
<td>1969 10</td>
<td>1976 10</td>
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<td>1141455</td>
<td>Castlegar A</td>
<td>1956 12</td>
<td>1968 04</td>
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<td>Dease Lake</td>
<td>1972 03</td>
<td>1968 04</td>
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<td>Fort St. John A</td>
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<td>Germensen Landing</td>
<td>1966 07</td>
<td>1979 06</td>
</tr>
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<td>1123970</td>
<td>Kelowna A</td>
<td>1973 05</td>
<td>1986 04</td>
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<td>Mackenzie A</td>
<td>1971 11</td>
<td>1986 04</td>
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<td>1025370</td>
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<td>1985 02</td>
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<td>1096450</td>
<td>Prince George A</td>
<td>1962 11</td>
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<td>Princeton A</td>
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<td>Puntzi Mountain</td>
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<td>3012205</td>
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<td>3012210</td>
<td>Edmonton Namado</td>
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<td>1987 04</td>
</tr>
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<td>3062244</td>
<td>Edsona</td>
<td>1970 05</td>
<td>1988 05</td>
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<td>3062693</td>
<td>Fort McMurray</td>
<td>1971 11</td>
<td>1988 11</td>
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<td>3035201</td>
<td>Pincher Creek</td>
<td>1962 09</td>
<td>1979 06</td>
</tr>
<tr>
<td>3015522</td>
<td>Rocky Mtn House</td>
<td>1978 04</td>
<td>1988 04</td>
</tr>
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<td>3066001</td>
<td>Slave Lake</td>
<td>1971 11</td>
<td>1988 11</td>
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<td>4060981</td>
<td>Buffalo Narrows</td>
<td>1975 12</td>
<td>1979 10</td>
</tr>
<tr>
<td>4061861</td>
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<td>1974 11</td>
<td>1986 04</td>
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<td>4012400</td>
<td>Estevin</td>
<td>1965 11</td>
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<td>Hudson Bay</td>
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<td>4075518</td>
<td>Nipawan A</td>
<td>1973 08</td>
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</tr>
<tr>
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Table B–2. Canadian data elements requested.

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<td>Dew point temperature</td>
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<td>075</td>
<td>Wind direction</td>
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<td>Wind direction</td>
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<tr>
<td>076</td>
<td>Wind speed</td>
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<tr>
<td>078</td>
<td>Dry bulb temperature</td>
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<tr>
<td>079</td>
<td>Wet bulb temperature</td>
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<tr>
<td>080</td>
<td>Relative humidity</td>
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<tr>
<td>081</td>
<td>Total cloud capacity</td>
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<tr>
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<td>Total cloud amount</td>
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<td>Daily minimum temperature</td>
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<td>Daily mean temperature</td>
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<td>RF4 net all wave radiation</td>
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<td>RF6 total upward radiation</td>
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