Large Scale Modelling of Hydrologic Response for Climate Impact Assessment and Flood Forecasting

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STATEMENT

The rainfall-runoff model IHACRES used in this thesis was developed by Professor A.J. Jakeman. Other parts of the thesis are due to the author unless otherwise indicated in the text.

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ABSTRACT

A lumped parameter rainfall-runoff model, IHACRES, is applied to the large upland area of the Goulburn, Ovens, Kiewa and Upper Murray Basins of the Murray-Darling Drainage Division, Australia, to predict streamflow under different climatic conditions. The total drainage area of the catchments modelled is about 13,500 km² and has a mean annual discharge of 5,583,000 ML. The thesis represents the first evaluation of this, and probably any other, daily rainfall-runoff model over so many contiguous catchments totalling such a large area. The analysis is comprehensive in terms of the number of catchments investigated and the number of calibration and simulation periods used in each catchment. The Basins are subdivided into 27 individual catchments (from 100 km² to 2,000 km²) each of which are calibrated separately. High values of model efficiency and low bias are consistently obtained for different calibration subperiods for all catchments in the Basins considered. Simulation tests are used to help select the best models for each catchment. The selected models allow simulation of the water regime during long historical periods when only climatological (rainfall and temperature) data were available. This procedure is extremely important for estimation of the effect of climate variability and of the possible impact of climate change on the hydrologic regime in the region and, in particular, for supporting irrigation management.

For those catchments located in the highest parts of the Australian alpine region, snow melt/accumulation processes feature prominently in the hydrological regime. Accordingly, a model was developed to compute equivalent rainfall from raw precipitation records, taking into consideration snow melt/accumulation processes in the different parts of these catchments. This model uses daily meteorological data as an input, determined on a daily basis over the whole region under consideration using a spatial interpolation procedure with a
The very high level of uncertainty should be indicated here. For instance, for the Kiewa River catchment flooding may increase to 62% for the 'most wet' scenario in 2030, whereas flow events higher than the selected magnitude may almost vanish for the 'most dry' scenario.
resolution of 2.5 km x 2.5 km. Daily streamflow for the snow-affected catchments was modelled using as an input the equivalent rainfall estimated by the snow melt/accumulation module and the mean daily temperature in each grid cell integrated over the whole catchments.

Climate scenarios for the years 2030 and 2070 were applied by transforming historical climate data. The daily temperatures were increased by a constant amount (1.5° to 5°) and daily precipitation intensities were scaled by a constant factor (-20% to +40%) but frequencies of relative precipitation were unchanged. Estimates of streamflow changes for these climate scenarios were produced for these periods for all Basins under consideration. Climate impacts were considered from two perspectives: impacts on the annual and monthly amount of water in the Basins, and impacts on the probability of extreme events such as floods and droughts. As the scenarios provide a range of possible changes in temperature and precipitation, two extreme cases were considered: ‘most dry’ and ‘most wet’ climatic changes for both future dates (2030 and 2070).

For the problem of estimating the impact of climatic change on the probability of extreme events, the conclusion is that, for the ‘most wet’ scenario, increases in the probabilities of stipulated flooding levels in the future are: about 50±10% at 2030 and 100±20% at 2070 for both snow-free and snow-affected types of catchments. The probabilities are slightly higher for snow affected regions. Drought frequency, as defined by a soil wetness index, increases about 35% to 40% for the ‘dry’ scenario at 2030 and 80% to 90% for this scenario at 2070 for both types of catchments.

A method of combining a conceptual rainfall-runoff model and a self-adaptive linear filtering approach was developed and applied to forecast daily streamflow for nine catchments in the
Upper Murray Basin. Considerable performance improvement was achieved compared with predictions based on the use of the conceptual model only or with 'naive' forecasts: the errors of the forecast 3-5 days forward for the combined method are comparable with the errors of a 1 day forward prediction provided by the conceptual model only.

The methodologies, models and databases developed provide a basis for future work on the effects of climate variability/change and land cover change on water supply regimes, particularly in the region studied. Improvements in estimates of mean climate change scenarios can easily be fed into the calibrated models as they become available, as can assumptions about the multivariate distribution of climate variables obtained for example with the aid of weather simulation models.

Recent work on the relationships between IHACRES model parameter values and landscape attributes suggests it should be possible to estimate the effects of land cover changes in the ungauged as well as the gauged catchments of the region. The parameter estimates obtained for the 27 catchments studied provide a starting point for assessing the accuracy of such a methodology.
TABLE OF CONTENTS

ACKNOWLEDGEMENTS........................................................................................................ iii

ABSTRACT ................................................................................................................................ v

CONTENTS .......................................................................................................................... viii

CHAPTER 1

INTRODUCTION..................................................................................................................... 1
  1.1. Background .................................................................................................................. 1
    1.1.1 Objectives of the thesis and rationale .................................................................. 1
    1.1.2 Scientific basis and contributions of the thesis .................................................. 3
    1.1.3 Review material .................................................................................................... 4
  1.2. Selection of the region ................................................................................................ 5
    1.2.1 Australia's surface water resources ..................................................................... 5
    1.2.2 Surface water resources of the Murray-Darling Drainage Division .................. 6
  1.3. Selection of the rainfall-runoff model ........................................................................ 10
    1.3.1 Overview of different types of hydrological model .......................................... 10
    1.3.2 Recent advances in surface runoff modelling .................................................. 14
    1.3.3 Review of IHACRES applications .................................................................... 18
  1.4. The climate change impact problem ........................................................................ 19
  1.5. Fast track and long term methodologies for predicting catchment hydrologic response ......................................................................................................................... 20
  1.6. Simplifications of the modelling approach ............................................................... 22

CHAPTER 2

MODELLING RAINFALL-RUNOFF FROM LARGE CATCHMENT TO BASIN SCALE: THE GOULBURN AND OVENS BASINS .................................................................................. 26

Summary ................................................................................................................................ 26

  2.1. Introduction ............................................................................................................... 27
  2.2. Goulburn Basin Description ....................................................................................... 28
  2.3. The Description of the Ovens Basins ....................................................................... 33
    2.3.1. Water resources and physiography ................................................................ 33
    2.3.2. Climatological data of the Ovens Basin ......................................................... 35
  2.4. The IHACRES mode ................................................................................................. 35
  2.5. Model performance in the Goulburn Basin and catchment response profiles ........ 37
    2.5.1. Upstream catchments ...................................................................................... 37
    2.5.2. The composite catchment ................................................................................ 43
    2.5.3. Downstream catchments .................................................................................. 46
    2.5.4. Sugarloaf Creek catchment .............................................................................. 47
  2.6. Selection of the best models (the Goulburn Basin) .................................................. 48
  2.7. Historical variability (the Big and Jamieson Rivers) ................................................. 51
  2.8. Model performance for the catchments of the Ovens Basin ................................... 55
CHAPTER 3

ESTIMATION OF POSSIBLE CLIMATE CHANGE IMPACTS ON WATER AVAILABILITY, EXTREME FLOW EVENTS AND SOIL MOISTURE IN THE GOULBURN AND OVEN BASINS

Summary .......................................................................................................................... 68

3.1. Introduction ..................................................................................................... 69
3.2. Climate scenarios ............................................................................................. 71
3.3. Climate impact on streamflow ........................................................................... 33
   3.3.1. Background .......................................................................................... 74
   3.3.2. Scaling of the model ........................................................................ 76
   3.3.3. Climate impact on annual and monthly streamflow ................. 77
   3.3.4. Extreme events .................................................................................. 85
3.4. Discussion ......................................................................................................... 91
3.5. Conclusions ....................................................................................................... 94

CHAPTER 4

RUNOFF MODELLING FOR SNOW-AFFECTED CATCHMENTS IN THE AUSTRALIAN ALPINE REGION

Summary .......................................................................................................................... 96

4.1. Introduction ..................................................................................................... 97
   4.1.1. Snow runoff models ........................................................................ 97
   4.1.2. Empirical models ............................................................................ 98
   4.1.3. Physical models ............................................................................... 100
   4.1.4. Distributed models .......................................................................... 103
   4.1.5. Comparison of different models .................................................. 104
   4.1.6. Water equivalent of snow ............................................................ 106
   4.1.7. Snow modelling in Australia and New Zealand ....................... 108
   4.1.8. The context ...................................................................................... 110
4.2. Description of the catchments .......................................................................... 110
4.3. The climatological data .................................................................................... 115
4.4. Model description ............................................................................................. 121
   4.4.1. Snow melt/accumulation module .................................................. 121
   4.4.2. Summary of the general procedure ............................................ 127
4.5. Results of snowmelt/accumulation and streamflow modelling .................. 129
   4.5.1. Snow melt/accumulation modelling ............................................ 129
   4.5.2. Results of snow runoff modelling ............................................... 133
4.6. Conclusions ....................................................................................................... 143
CHAPTER 5

COMPARATIVE ANALYSIS OF CLIMATE IMPACT ON WATER AVAILABILITY AND EXTREME EVENTS FOR SNOW-FREE AND SNOW-AFFECTED CATCHMENTS OF THE MURRAY-DARLING BASIN ......................................................... 144

Summary ........................................................................................................................ 144
  5.1. Introduction ............................................................................................................... 146
  5.2. The region under consideration .............................................................................. 148
  5.3. The climate scenarios and transformation of the climatic time series .......... 149
  5.4. Climate impact on annual and monthly streamflow ........................................ 150
  5.5. Climate impact on extreme events: floods and droughts .................................. 160
  5.6. Discussion and conclusions ................................................................................ 166
  5.7. Appendix Transforming climatic data in snow-affected catchments? .............. 172

CHAPTER 6

A DETERMINISTIC-STOCHASTIC STREAMFLOW FORECASTING ALGORITHM AND ITS APPLICATION TO THE UPPER MURRAY BASIN ........................................................................ 174

Summary ....................................................................................................................... 175
  6.1. Introduction ............................................................................................................. 175
    6.1.1. Background ...................................................................................................... 175
    6.1.2. The Upper Murray Basin description ............................................................. 179
  6.2. Results of runoff modelling (snow-free catchments) ....................................... 181
    6.2.1. The Tallangatta and Cudgewa Creek catchments ........................................... 181
    6.2.2. The Jingellic Creek catchment ....................................................................... 182
  6.3. Results of runoff modelling (snow-affected catchments) ............................... 187
    6.3.1. The Mitta-Mitta River catchment ................................................................. 187
    6.3.2. The Upper Murray at Biggara, Gibbo River and Snowy Creek catchments ............................................................................. 187
    6.3.3. The Tooma and Big River catchments ......................................................... 193
  6.4. Modelling on a 4-hourly time step .................................................................... 201
  6.5. Forecasting algorithms ...................................................................................... 203
    6.5.1. Structure of the forecasting algorithm ......................................................... 203
    6.5.2. Deterministic part (IHACRES) .................................................................... 208
    6.5.3. Stochastic part (ARIMA) .............................................................................. 210
    6.5.4. Application of the ARIMA model ............................................................... 210
    6.5.5. Results and analysis ..................................................................................... 211
  6.6. Discussion and conclusions .............................................................................. 216
CHAPTER 7

CONCLUSIONS ........................................................................................................ 217

Summary ...................................................................................................................... 217
  7.1. General structure of the work implemented .................................................... 217
  7.2. Rationale ............................................................................................................ 218
  7.3. Methodological aspects ................................................................................... 219
  7.4. Inventory of results ........................................................................................ 224
  7.5. Future work ..................................................................................................... 229

REFERENCES ........................................................................................................... 232
<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Water resources of the Australian Drainage Divisions</td>
<td>7</td>
</tr>
<tr>
<td>1.2</td>
<td>Areas and mean annual discharge of the Basins of the Murray Darling Drainage Division</td>
<td>9</td>
</tr>
<tr>
<td>2.1</td>
<td>The catchments upstream of Lake Eildon (Victorian Surface Water Information, 1984)</td>
<td>32</td>
</tr>
<tr>
<td>2.2</td>
<td>The catchments downstream of Lake Eildon (Victorian Surface Water Information, 1984)</td>
<td>32</td>
</tr>
<tr>
<td>2.3</td>
<td>Model efficiency values (see definition in Section 2.5.1) for calibration of the upstream catchments</td>
<td>41</td>
</tr>
<tr>
<td>2.4</td>
<td>Simulation statistics with two-year calibrated models over period 1975-1990 for the upstream catchments. (model efficiency), E and Bias (mean daily error in cumecs). Bold values denote the best selected models (see Section 2.6) for each catchment.</td>
<td>44</td>
</tr>
<tr>
<td>2.5</td>
<td>E values for calibration results for downstream catchments</td>
<td>46</td>
</tr>
<tr>
<td>2.6</td>
<td>Simulation over whole period for the downstream catchments. E and Bias (mean daily error in cumecs), Bold values denote the best selected model for downstream catchments.</td>
<td>47</td>
</tr>
<tr>
<td>2.7</td>
<td>Catchments of the Ovens Basin (Victorian Surface Water Information, 1984)</td>
<td>55</td>
</tr>
<tr>
<td>2.8</td>
<td>Model efficiency values E for calibration of the catchments of the Ovens Basin</td>
<td>58</td>
</tr>
<tr>
<td>2.9</td>
<td>Simulation with two-year calibrated models over the period 1969-1985 for the Ovens Basin catchments. E (model efficiency) and Bias (mean daily absolute error in cumecs). Bold values denote the best selected models for each catchment.</td>
<td>59</td>
</tr>
<tr>
<td>3.1</td>
<td>Climate scenarios for the Victorian Alps</td>
<td>74</td>
</tr>
<tr>
<td>3.2</td>
<td>Climate impact on annual precipitation and streamflow for selected scenarios. The Goulburn Basin (upper part). The Goulburn (lower part). The Ovens Basin</td>
<td>77</td>
</tr>
<tr>
<td>4.1</td>
<td>The catchments under consideration (Victorian Surface Water Information, 1984)</td>
<td>115</td>
</tr>
<tr>
<td>4.2</td>
<td>Model efficiency values E for calibration of the snow runoff model for the Kiewa and Mitta-Mitta catchments.</td>
<td>136</td>
</tr>
</tbody>
</table>
4.3. Simulation with nine two year calibrated models over whole period of observation for the Kiewa and Mitta-Mitta catchments. $E$ and Bias (mean daily error in cumecs). Bold values denote the best selected model. ........................................................................................................... 139

5.1. Climate impact on annual precipitation and streamflow for selected scenarios in the snow-affected catchments. The Mitta-Mitta catchment. The Kiewa catchment. .......................................................................................... 151

6.1. The catchments of the Upper Murray Basin selected for modelling/forecasting. .......................................................................................................................... 181

6.2. Model efficiency values $E$ for calibration of the IHACRES model for the Tallangatta and Cudgewa Creeks catchments. ........................................................................................................... 183

6.3. Model efficiency values $E$ for calibration of the rainfall-runoff model for the Jingellic Creek catchment. ........................................................................................................... 183

6.4. Model efficiency values $E$ for calibration of snow runoff for the Upper Murray, Gibbo Rivers and Snowy Creek catchments. ........................................................................................................... 188

6.5 Simulation results over the 10 year period from 01/01/1977. .......................................................................................................................... 193

6.6 Model efficiency values $E$ for calibration of snow runoff for the Tooma River. .......................................................................................................................... 194

6.7. Model efficiency values $E$ for calibration of snow runoff for the Big River. .......................................................................................................................... 197

6.8. Simulation results over the 14-year period from 01/01/1973 for the Tooma River. Bold values denote the best selected model. ........................................................................................................... 199

6.9. Simulation results over the 20-year period from 01/01/1965 for the Big River. Bold values denote the best selected model. ........................................................................................................... 199

6.10. The mean absolute and mean square forecast errors obtained for a range of ARIMA parameters and three different conceptual models. "*" means model diverges. ........................................................................................................... 214

6.11. The quality of forecast obtained for the linearly filtered ARIMA(1,0,0) residuals of the conceptual model SRIV IHACRES. The mean absolute and mean square errors are given. ........................................................................................................... 214

6.12. Efficiency statistics ($E$) and Bias for long-term simulations period for all 9 catchments considered. The results of the IHACRES simulation and IHACRES combined with an ARIMA algorithm are presented. ........................................................................................................... 215
LIST OF FIGURES

1.1. The Drainage Divisions of Australia (Department of Primary Industries and Energy, 1987) ................................................................. 6

1.2. The Basins of the Murray Darling Drainage Division (Fleming, 1982) ................................................................. 8

2.1a. River network, meteorological and discharge stations for the catchments under consideration in the Goulburn Basin ............................ 29

2.1b. River network, meteorological and discharge stations for the catchments under consideration in the Ovens Basin ........................................ 30

2.2. Observed (solid line), modelled (dashed line) streamflow (cumecs) and error for calibration period 6 (1981-1982) for all 6 upstream catchments ............................................................... 39

2.2. (continued) Observed (solid line), modelled (dashed line) streamflow (cumecs) and error for calibration period 6 (1981-1982) for all 6 upstream catchments ............................................................... 40

2.3. Response profiles of three rivers upstream of Lake Eildon, using parameters estimated in calibration period 6. The Jamieson River (left) is the wettest catchment, the Howqua River (centre) has the mean level of humidity and the Delatite River (right) is the driest of the three ......................................................................................................... 42

2.4. Total streamflow model fit and error (below) for a composite catchment (left) and the sum of modelled streamflow for the five individual upstream catchments (right) ........................................................................ 45

2.5. Observed (solid line), modelled (dashed line) streamflow and error (below) for calibration period 6 (1981-1982) and 7 (1983-1984, for Sugarloaf Creek) for 6 downstream catchments ............................................................... 49

2.5. (continued) Observed (solid line), modelled (dashed line) streamflow and error (below) for calibration period 6 (1981-1982) and 7 (1983-1984, for Sugarloaf Creek) for 6 downstream catchments ............................................................... 50

2.6. Mean monthly observed (circles) and modelled (squares) discharge (1000 ML) shown for the Goulburn River at Dohertys and Jamieson River. Upper row - monthly discharge distributions, lower row - modelled values against observed values; 1:1 line is shown ......................................................................................................... 52
2.7a. Simulation on the basis of long term historical climatological data for the Big River. 5-year running mean values are calculated for precipitation (above), temperature (middle) and the best model (below). The mean values for two historical periods (1890-1945 and 1945-1990) are shown. .......................................................... 53

2.7b. Simulation on the basis of long term historical climatological data for the Jamieson River catchment. 5-year running mean values are calculated for precipitation (above), temperature (middle) and the best model (below). The mean values for two historical periods (1890-1945 and 1945-1990) are shown. .......................................................... 54

2.8. Mean annual values for a 90-year period simulation of the catchment wetness index $s_k$ in 4 upstream catchments. .......................................................... 56

2.9. Observed (solid line), modelled (dashed line) streamflow (cumecs) and error for calibration period 3 (1973-1975) for 3 catchments of the Ovens Basin .......................................................... 60

2.10. Simulation of discharge on the basis of long term historical climate data for the Goulburn catchments upstream of Lake Eildon. 5-year running mean values are shown for precipitation (above), temperature (middle), discharge and the best model of streamflow (below). .......................................................... 62

2.11. Simulation of discharge on the basis of long term historical climate data for the Goulburn catchments downstream of Lake Eildon. 5-year running mean values are shown for precipitation (above), temperature (middle), discharge and the best model of streamflow (below). .......................................................... 63

2.12. Simulation of discharge on the basis of long term historical climate data for the catchments of the Ovens Basin. 5-year running mean values are shown for precipitation (above), temperature (middle), discharge and the best model of streamflow (below). .......................................................... 64

2.13. The mean relative errors for aggregated flow of the Ovens Basin obtained using the 6 best models for all 5 rivers of the Ovens Basin. The rank of the model along the horizontal axis is from lowest to highest. .......................................................... 66

3.1. Scenarios for future global warming from Wigley and Raper (1992) .......................................................... 72

3.2. The sub-regions used for winter rainfall change from CIG (1992) .......................................................... 73

3.3. Streamflow response to the changes in (a) temperature and (b) precipitation for the Ovens Basin .......................................................... 78
3.4a. Climate impact on annual streamflow for the 4 scenarios listed in Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered provisionally as upper and lower thresholds for possible annual streamflow fluctuations for future climate change. (The catchments of the Goulburn Basin upstream of Lake Eildon) ........................................... 80

3.4b. Climate impact on annual streamflow for the 4 scenarios listed in Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered provisionally as upper and lower thresholds for possible annual streamflow fluctuations for future climate change (The catchments of the Goulburn Basin downstream of Lake Eildon.) ........................................... 81

3.4c. Climate impact on annual streamflow for the 4 scenarios listed in Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered provisionally as upper and lower thresholds for possible annual streamflow fluctuations for future climate change. (The catchments of the Ovens Basin) ........................................... 82

3.5. Climate impact on monthly streamflow in the Ovens Basin for 2070 scenarios from Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered provisionally as upper and lower thresholds for possible February and August streamflow fluctuations for future climate change. Dashed line - measured streamflow ........................................... 83

3.6. Climate impact on mean monthly discharge for the catchments of the Goulburn Basin downstream of Lake Eildon ........................................... 84

3.7a. Histograms of daily streamflow (for a period of August, September and October) for the present and the 2030 and 2070 ‘most dry’ scenarios for the Upper Ovens River at Bright (403205) ........................................... 86

3.7b. Histograms of daily streamflow (for a period of August, September and October) for the present and the 2030 and 2070 ‘most wet’ scenarios for the Upper Ovens River at Bright (403205) ........................................... 87

3.8a. Histograms for soil wetness index for present and the 2030 and 2070 ‘most dry’ scenarios. The case of the Upper Ovens River at Bright (403205) is considered ........................................... 89

3.8b. Histograms for soil wetness index for present and the 2030 and 2070 ‘most wet’ scenarios. The case of the Upper Ovens River at Bright (403205) is considered ........................................... 90

3.9. The distribution, according to its average temperature class, of mean daily flow for the observed data and the model simulation over the 45 year period (1945 to 1990) for the Upper Ovens River at Bright (403205). Mean daily flow was calculated separately for each temperature interval with a class width of one degree ........................................... 92
4.1. River network, meteorological and discharge stations for the catchments under consideration in the Kiewa Basin and the Mitta-Mitta catchment of the Upper Murray Basin. ............................................................... 112

4.2a. Annual measured (solid line) and interpolated rainfall (dashed line) for the Omeo, for the period 1965-84. .................................................................................. 118

4.2b. Annual measured (solid line) and interpolated rainfall (dashed line) for the Tawonga station for the period 1965-84. ..................................................................... 119

4.2c. Annual measured (solid line) and interpolated rainfall (dashed line) for the Rocky Valley station for the period 1965-84. .............................................................. 120

4.3a. An example of monthly measured (solid line) and interpolated (dashed line) rainfall for the Benambra station. .................................................................................. 122

4.3b. An example of monthly measured (solid line) and interpolated (dashed line) rainfall for the Omeo station. .................................................................................. 123

4.4. The probability that precipitation will fall as snow for the Victorian alpine region (from Ruddell et al., 1990). ................................................................. 125

4.5. The diagram illustrating the algorithm of snow runoff modelling. .............................. 128

4.6. Long term mean values of monthly streamflow of the Mitta-Mitta River (circles), of measured precipitation interpolated over the Mitta-Mitta catchment (diamonds), and of monthly equivalent rainfall, obtained from the snow melt/accumulation model (triangle). .................................................. 130

4.7a. Measured (solid line) and equivalent (dashed line) rainfall for the Rocky Valley station (elevation 1652 m a.s.l.), where snow melt/accumulation processes are substantial. ......................................................... 131

4.7b. Measured (solid line) and equivalent (dashed line) rainfall for the Tawonga station with low elevation 314 m a.s.l., where snow melt/accumulation processes are almost negligible. ......................................................... 132

4.8. Observed and modelled snow depth for the Falls Creek station at 1984. ......................... 134

4.9. Observed and modelled maximum snow depth at the Rocky Valley Station for the period 1965-1984. ................................................................. 135

4.10a. Observed (solid line), modelled (dashed line) streamflow (cumecs) and error for calibration period 8 (1980-1982) for the Kiewa catchments. ................................. 137

4.10b. Observed (solid line), modelled (dashed line) streamflow (cumecs) and error for calibration period 8 (1980-1982) for the Mitta-Mitta catchment. ................................. 138
4.11a. Simultion over 19-year period for the model calibrated on CP2 (Table 4.2) and long term historical climatological data for the Kiewa catchment. Mean values for precipitation (above), temperature (middle) and the observed and modelled flow (below) are shown for the annual data ................................................................. 140

4.11b. Simulation over 19-year period (1965-1984) for the model calibrated on CP2 (Table 4.2) and long term historical climatological data for the Kiewa catchment. Mean values for precipitation (above), temperature (middle) and the observed and modelled flow (below) are shown for July, when accumulation prevails .............................................................................................................. 141

4.11c. Simulation over 19-year period (1965-1984) for the model calibrated on CP2 (Table 4.2) and long term historical climatological data for the Kiewa catchment. Mean values for precipitation (above), temperature (middle) and the observed and modelled flow (below) are shown for October, when snowmelt prevails ............................................................................................................. 142

5.1a. (The Kiewa River). Climate impact on annual streamflow for the 4 scenarios listed in Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered as upper and lower thresholds for possible annual streamflow fluctations for future climate change .............................................................................................................................. 152

5.1b. (The Mitta-Mitta River). Climate impact on annual streamflow for the 4 scenarios listed in Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered as upper and lower thresholds for possible annual streamflow fluctations for future climate change .............................................................................................................................. 153

5.2a. Climate impact on monthly streamflow in the Ovens Basin for 2070 scenarios from Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered as upper and lower thresholds for possible monthly streamflow fluctuations for future climate change .............................................................................................................................. 154

5.2b. Climate impact on monthly streamflow the Kiewa Basin for 2070 scenarios from Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered as upper and lower thresholds for possible monthly streamflow fluctuations for future climate change .............................................................................................................................. 155

5.3a. Climate impact (in percent) on the mean monthly discharge for the snow-free catchments of the Goulburn Basin downstream of Lake Eildon .............................................................................................................................. 156

5.3b. Climate impact (in percent) on the mean monthly discharge for the snow-affected Kiewa catchment .............................................................................................................................. 158
5.4. Two cases of climate impact on the annual distribution of mean monthly discharge for (left column) the snow-free catchments of the Ovens River, ‘most dry’ and ‘most wet’ scenario for 2070, and (right column) the snow-affected Mitta-Mitta catchment, ‘most dry’ and ‘most wet’ scenario for 2070 .................................................. 159

5.5a. Histograms for daily streamflow (for the period of August, September and October) for the present and the 2030 and 2070 ‘most dry’ scenarios for the snow-affected Kiewa catchment ........................................ 161

5.5b. Histograms for daily streamflow (for the period of August, September and October) for the present and the 2030 and 2070 ‘most wet’ scenarios for the snow-affected Kiewa catchment ........................................ 162

5.6a. Histograms for soil wetness index for present and the 2030 and 2070 (a) ‘most dry’ scenarios for the Kiewa River at Mongans Bridge ........................................ 164

5.6b. Histograms for soil wetness index for present and the 2030 and 2070 ‘most wet’ scenarios for the Kiewa River at Mongans Bridge ........................................ 165

5.7. Proportional annual losses for the snow-free Ovens River catchment (above) and the snow-affected Kiewa River catchment (below). The regression lines of proportional losses against annual precipitation are indicated ........................................ 170

6.1. River network, meteorological and discharge stations for the catchments under consideration in the Upper Murray Basin ........................................ 180

6.2. Observed (solid line), modelled (dashed line) streamflow (cumecs) for CP 5 (1980-1981) for the Tallangatta Creek catchment ........................................ 183

6.3. Observed (solid line), modelled (dashed line) streamflow (cumecs) for the CP 5 (1980-1981) for the Cudgewa Creek catchment ........................................ 184

6.4. Observed (solid line), modelled (dashed line) streamflow (cumecs) for CP 8 (1986-1987) for the Jingellic Creek catchment ........................................ 185

6.5. Observed (solid line), modelled (dashed line) streamflow (cumecs) for CP 7 (1985-1986) for the Upper Murray River catchment ........................................ 189

6.6. Observed (solid line), modelled (dashed line) streamflow (cumecs) for the CP 4 (1979-1980) for the Gibbo River catchment ........................................ 190

6.7 Observed (solid line), modelled (dashed line) streamflow (cumecs) for the CP 7 (1985-1986) for the Snowy Creek catchment ........................................ 191

6.8 Observed (solid line), modelled (dashed line) streamflow (cumecs) for simulation results over the period 1978-1980 for the Snowy Creek catchment ........................................ 192
6.9. Observed (solid line), modelled (dashed line) streamflow (cumecs) for CP 7 (1985-1986) for the Tooma River catchment. ......................................................... 195

6.10. Observed (solid line), modelled (dashed line) streamflow (cumecs) for CP 1 (1966-1967) for the Big River catchment. ......................................................... 196

6.11. Observed (solid line), modelled (dashed line) streamflow (cumecs) for simulation results over the period 1966-1967 for the Big River catchment. ...................................................................................... 197

6.12. Historical simulation of annual streamflow for the Tallangatta and Cudgewa Creeks using the IHACRES model. .................................................................................................................. 200

6.13. Observed (solid line), modelled (dashed line) streamflow (cumecs) using a 4-hourly time step calibration for the Tallangatta Creek catchment (summer) over a 90 day period. .............................................................................................................. 202

6.14. Observed (solid line), modelled (dashed line) streamflow (cumecs) using a 4-hourly time step for the Tallangatta Creek catchment (winter) over a 90 days period. ...................................................................................................................... 204

6.15. Observed (solid line), modelled (dashed line) streamflow (cumecs) for simulation results using a 4-hourly time step for the Tallangatta Creek catchment over a 300 day period. ........................................................................................................ 205

6.16. Observed (solid line), modelled (dashed line) streamflow (cumecs) using a 4-hourly time step for the Tallangatta Creek catchment over a 300 day period (calibration). .............................................................................................................. 206

6.17. Observed (solid line), modelled (dashed line) streamflow (cumecs) using a 4-hourly time step for the Tallangatta Creek aggregated to the daily time step. .............................................................................................................. 207

6.18. 1-day ahead forecast for a low flow period in the Tallangatta Creek catchment. ................................................................................................................................. 212

6.19. 1-day ahead forecast for a high flow period in the Tallangatta Creek catchment. ................................................................................................................................. 213
CHAPTER 1

INTRODUCTION

1.1. Background

1.1.1. Objectives of the thesis and rationale

The main objective of this thesis is the development of a methodology for analysis of large scale daily hydrological response and its testing in four Basins in the south-eastern part of the Murray Darling Drainage Division (MDDD) for predictive and forecasting purposes. In particular it concerns:

1. Identification of an adequate hydrological model allowing determination of daily streamflow behaviour using historical precipitation, temperature and stream discharge data, and information on the physical properties of the catchments under consideration.

2. An assessment of potential impacts at small and large catchment scale of a range of climate change scenarios, due to the enhanced greenhouse effect (related to industrially induced gases emitted into the atmosphere), on runoff and water availability in the area considered; assessment is provided particularly for the impact of climate change on the frequency of extreme events such as floods and droughts, as well as on annual flow regimes.

3. Development of methods to treat snow affected areas located in the Australian alpine region, which take into consideration snow melt/accumulation processes.
4. Development of an operational flood forecasting system for rivers of the Upper Murray Basin in order to support management by the Murray Darling Basin Commission of Australia’s two major reservoirs, Lake Hume and Lake Dartmouth.

Estimation of possible climatic impacts on water availability, especially for irrigation, and on the frequency of extreme events is a concern of regulatory and management authorities. The MDDD is one of the most significant producers of food in Australia. In 1980-81 the area under crop in this region was 46% of the national total (Nix, 1982). The upper tributaries of the Murray Rivers, chosen for the study here, are extremely important suppliers of water to the whole agricultural region of south-western New South Wales and Victoria. Particular data about water use in the Basins considered can be found in the relevant chapters of this thesis.

Estimation of possible climate impacts is also important in terms of possible changes in drought frequency in these regions. The economic impact of severe drought cannot be overestimated, and even at present drought losses in Australia amount to hundreds of million dollars. For instance, Australia’s overall crop production was down by 31% after the drought of 1982/83 (Smith et al., 1992). Flood frequency and magnitude analysis is also quite important because large floods usually accelerate soil erosion processes which can severely affect fertility and, consequently, agricultural production levels in the region. Another economic (and social) aspect of this problem is dam security management and mitigation of urban flooding impacts. The importance of estimating possible climate impacts on streamflow regimes is discussed in more detail in Section 1.4.
1.1.2. Scientific basis and contributions of the thesis

The following scientific background summarises the basis of the present work:

(a) A conceptual lumped parameter rainfall-runoff model IHACRES, developed at the Centre for Resource and Environmental Studies, Australian National University, was used as a tool for modelling streamflow in the selected Basins. The successful worldwide application of this model, across many hydroclimatic regimes and scales, and its relative conceptual simplicity (see Section 1.3.3) were the basis for its selection as a modelling tool;

(b) Mean climate scenarios developed at the CSIRO Division of Atmospheric Research, based on scenarios of future global warming produced by Wigley and Raper (1992) and the regional results of five recent Global Climate Model (GCM) equilibrium experiments (including two GCMs from CSIRO and the Australian Bureau of Meteorology), were employed as a simple methodology to transform historic temperature and precipitation data in order to use them as input to the IHACRES model for estimating possible climate change impact; and

(c) Observed data on temperature, precipitation, streamflow and snow depth were available for the region under study due to the efforts of the Bureau of Meteorology, the Rural Water Commission of Victoria, the NSW Department of Land and Water Conservation and the Murray Darling Basin Commission.

This study represents the first modelling analysis of the surface water regime of these four Basins in the MDDD (The Goulburn, Ovens, Kiewa and Upper Murray). It is also perhaps the first time that a lumped conceptual rainfall-runoff model, and certainly IHACRES, has been applied daily over so many contiguous catchments (27) totalling such a large area
(13,500 km²). The snow melt/accumulation model was developed and successfully tested in the snow-affected area of the Basins considered. The flood forecasting system, based on a method of coupling the deterministic (IHACRES) and stochastic (ARIMA linear filtering) models, was developed and applied for streamflow forecasting for the upstream catchments of Australia’s two major reservoirs. Another contribution of this thesis is an estimation of possible climate impact of water availability and extreme events, based on the use of the climatic data obtained from different climate scenarios developed in the Division of Atmospheric Research CSIRO as model input.

1.1.3. Review material

Reviews of the scientific publications relevant to the thesis are structured as follows: a review of recent advances in hydrological modelling is placed in this Introduction (Sections 1.3.2 and 1.3.3); a review of previous climate impact studies is given in the introductory section of Chapter 3 and of snow modelling in the introductory section of Chapter 4; a review of forecasting methods is provided in the introductory section of Chapter 5.

Many of the results described in this thesis have been published or submitted for publication as follows:


Chapter 3 - Schreider et al. (1996b), Jakeman et al. (1994b, 1995)

Chapter 4 - Schreider et al. (1995c, 1996d)

Chapter 5 - Schreider et al. (1996c), Schreider et al. (1996e)

Chapter 6 - Schreider et al. (1995b), Schreider et al. (1996f)
1.2. Selection of the region

1.2.1. Australia's surface water resources

Surface water is the most important source of water supply in Australia, providing more than 80% of total water consumption in the country. An overview of Australian surface water resources is given by Brown (1983), Department of Primary Industries and Energy (1987), and the latter is updated in Bergman (1989).

The Australian continent and Tasmania have been divided into 12 Drainage Divisions. These Divisions are shown in Figure 1.1 while their area, mean annual discharge and developed water resources are given in Table 1.1. Although some Drainage Divisions provide high yield (the Timor Sea, Gulf of Carpentaria and North-East Coast Divisions provide more than 60% of Australian surface water resources), they are located in relatively low populated areas with a lack of suitable agricultural land, which limits their potential for development. The MDDD is the most developed Division in Australia and is extremely important for Australian rural industry. Irrigation water consumption in Australia is approximately 10,240,000 ML which is about 70% of total water consumption. Irrigation water consumption in the MDDD is 8,710,000 ML/year.

An important characteristic of the Australian river flow regime is its high annual variability compared with other regions of the world. Therefore, Australian water storage, for a given demand from a given mean annual flow, must be eleven times larger than is required in Europe and six times higher than that in the USA in order to secure consumption levels (McMahon, 1975). Relief in the MDDD, especially in its south-eastern part, has permitted the building of large reservoirs. Three such artificial lakes, Dartmouth, Hume and Eildon, are located in our study area.
Figure 1.1. The Drainage Divisions of Australia (Department of Primary Industries and Energy, 1987).

1.2.2. Surface water resources of the Murray Darling Drainage Division

The MDDD has been divided into 26 Basins (Figure 1.2). The water resources of these Basins are summarised in Table 1.2 (Fleming, 1982, updated by information from Water Victoria, 1989). The more accurate values given for the Basins located in the Victorian part
Table 1.1. Water resources of the Australian Drainage Divisions (Department of Primary Industries and Energy, 1987).

<table>
<thead>
<tr>
<th>Drainage Division</th>
<th>Area (km²)</th>
<th>Mean annual runoff (1000 ML)</th>
<th>Developed resources (1000 ML) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>South-East Coast II</td>
<td>274,000</td>
<td>41,900</td>
<td>3,540 (4)</td>
</tr>
<tr>
<td>III</td>
<td>68,200</td>
<td>52,900</td>
<td>4,280 (10)</td>
</tr>
<tr>
<td>Murray Darling IV</td>
<td>1,060,000</td>
<td>24,300</td>
<td>1,020 (2)</td>
</tr>
<tr>
<td>South Australian Gulf V</td>
<td>82,300</td>
<td>877</td>
<td>10,000 (41)</td>
</tr>
<tr>
<td>South-West Coast VI</td>
<td>315,000</td>
<td>6,670</td>
<td>118 (13)</td>
</tr>
<tr>
<td>Indian Ocean VII</td>
<td>519,000</td>
<td>3,960</td>
<td>385 (6)</td>
</tr>
<tr>
<td>Timor Sea VIII</td>
<td>547,000</td>
<td>80,700</td>
<td>27 (-)</td>
</tr>
<tr>
<td>Gulf of Carpentaria IX</td>
<td>641,000</td>
<td>92,500</td>
<td>1,980 (2)</td>
</tr>
<tr>
<td>Lake Eyre X</td>
<td>1,170,000</td>
<td>6,310</td>
<td>78 (-)</td>
</tr>
<tr>
<td>Bulloo-Bancannia XI</td>
<td>101,000</td>
<td>1,090</td>
<td>26 (-)</td>
</tr>
<tr>
<td>Western Plateau XII</td>
<td>2,450,000</td>
<td>1,580</td>
<td>0 (-)</td>
</tr>
<tr>
<td>Total</td>
<td>7,680,000</td>
<td>397,000</td>
<td>21,500 (5)</td>
</tr>
</tbody>
</table>

of the MDDD can be explained by the fact that the boundaries for these Basins are better defined than those located in the northern part of the MDDD where relief is smoother and boundaries cannot be identified accurately. Some sources provide slightly (maximum 10%) different values for the Basin areas and discharge (c.f. Map of Murray Darling Basin, 1995).
Rural industry is very efficiently developed in the MDDD, and it is the most important region of Australia from this point of view. In the northern part of the MDDD surface and ground water resources are used for irrigation, whereas in the south-eastern part of the MDDD, especially in the state of Victoria, water use is dominated by surface water for irrigation. One
Table 1.2. Areas and mean annual discharge of the Basins of the Murray Darling Drainage Division (Fleming, 1982; Water Victoria, 1989)

<table>
<thead>
<tr>
<th>N</th>
<th>Basin</th>
<th>Area (km²)</th>
<th>Mean annual runoff (1000 ML)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Upper Murray</td>
<td>15,300</td>
<td>3,920</td>
</tr>
<tr>
<td>2</td>
<td>Kiewa</td>
<td>1,985</td>
<td>705</td>
</tr>
<tr>
<td>3</td>
<td>Ovens</td>
<td>7,779</td>
<td>1,620</td>
</tr>
<tr>
<td>4</td>
<td>Broken</td>
<td>7,724</td>
<td>325</td>
</tr>
<tr>
<td>5</td>
<td>Goulburn</td>
<td>16,192</td>
<td>3,040</td>
</tr>
<tr>
<td>6</td>
<td>Campaspe</td>
<td>4,179</td>
<td>280</td>
</tr>
<tr>
<td>7</td>
<td>Loddon</td>
<td>15,320</td>
<td>250</td>
</tr>
<tr>
<td>8</td>
<td>Avoca</td>
<td>12,352</td>
<td>85</td>
</tr>
<tr>
<td>9</td>
<td>Murray - Riverina</td>
<td>16,300</td>
<td>120</td>
</tr>
<tr>
<td>10</td>
<td>Murrumbidgee</td>
<td>84,000</td>
<td>3,200</td>
</tr>
<tr>
<td>11</td>
<td>Lake George</td>
<td>1,000</td>
<td>60</td>
</tr>
<tr>
<td>12</td>
<td>Lachlan</td>
<td>84,700</td>
<td>1,330</td>
</tr>
<tr>
<td>13</td>
<td>Benanee</td>
<td>21,400</td>
<td>50</td>
</tr>
<tr>
<td>14</td>
<td>Mallee</td>
<td>52,000</td>
<td>0</td>
</tr>
<tr>
<td>15</td>
<td>Wimmera - Avon</td>
<td>21,400</td>
<td>230</td>
</tr>
<tr>
<td>16</td>
<td>Border Rivers</td>
<td>49,500</td>
<td>900</td>
</tr>
<tr>
<td>17</td>
<td>Moonie</td>
<td>15,800</td>
<td>150</td>
</tr>
<tr>
<td>18</td>
<td>Gwydir</td>
<td>25,900</td>
<td>790</td>
</tr>
<tr>
<td>19</td>
<td>Namoi</td>
<td>43,000</td>
<td>760</td>
</tr>
<tr>
<td>20</td>
<td>Castlereagh</td>
<td>17,700</td>
<td>280</td>
</tr>
<tr>
<td>21</td>
<td>Macquarie - Bogan</td>
<td>73,300</td>
<td>1,470</td>
</tr>
<tr>
<td>22</td>
<td>Condamine - Culgoa</td>
<td>150,200</td>
<td>1,930</td>
</tr>
<tr>
<td>23</td>
<td>Warrego</td>
<td>72,800</td>
<td>440</td>
</tr>
<tr>
<td>24</td>
<td>Paroo</td>
<td>76,200</td>
<td>280</td>
</tr>
<tr>
<td>25</td>
<td>Darling</td>
<td>115,900</td>
<td>30</td>
</tr>
<tr>
<td>26</td>
<td>Lower Murray</td>
<td>58,800</td>
<td>110</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>1,060,000</td>
<td>22,350</td>
</tr>
</tbody>
</table>

of the largest irrigation districts in Australia is the Goulburn-Murray (encompassing areas of the Loddon, Campaspe, Goulburn and Broken Basins) and it is almost completely irrigated by surface water. Therefore, the decision to select the eastern region of the Victorian part of the MDDD for consideration in this thesis is explained by the significance of the surface water resources of this area for Australian agriculture.

Ten of the 26 Basins of the MDDD belong to the state of Victoria. Two of them, the Upper Murray and Mallee Basins, are crossed by state borders, with New South Wales and South
Australia, respectively. Total mean annual discharge of the Victorian part of the MDDD is more than 10,000,000 ML which constitutes about a half of the total discharge of the state of Victoria. The four selected Basins of the Goulburn, Ovens, Kiewa and Upper Murray River are located in the eastern section of the Victorian part of the MDDD and in general are the major suppliers of water for the lower Basins. The Murray-Goulburn irrigation district is the major single recipient of the water resources of these Basins. Victoria’s three largest reservoirs are located in this area: Lake Eildon in the Goulburn Basin and Lakes Dartmouth and Hume in the Upper Murray Basin. These four Basins provide more than 9,400,000 ML of annual flow, which constitutes about 95% of the total discharge of the Basins in the Victorian part of the MDDD. A description of the climatology, physiography and water resources of the selected Basins is given in relevant sections of Chapters 2, 4 and 6.

It is important to note that for a totally comprehensive analysis of surface water resources in the south-eastern part of the MODD, modelling of the Murrumbidgee Basin of the MDDD and the Snowy River Basin of the South-East Coast Division (part of its water is exported to the Upper Murray Basin) could be considered as a logical continuation of the present work.

1.3. Selection of the rainfall-runoff model

1.3.1. Overview of different types of hydrological models

There are three types of rainfall-runoff models which could be considered for predicting the stream discharge effects of climatic variations: empirical, physically-based and conceptual. Wheater et al. (1993) discuss the advantages and limitations of each type. Basically, empirical models contain too little process description to be used to make predictions on independent periods not used for model calibration. An example of an empirical model is the original unit hydrograph of Sherman (1936). Physically based models are too computationally demanding...
to be used on a catchment of more than a few square kilometres. An example of a physically based model is SHE (Abbot et al., 1986) which incorporates continuum mechanics type expressions for transit of water via surface runoff, the unsaturated and saturated zones to stream. Beven (1989) discusses other problems with physically based models. He mentions that such models are a powerful compilation of the relevant idealistic processes, but raise a number of important issues. The major problem is their description of subsurface processes because of the heterogeneity of soil structure. Conceptual models, on the other hand, can work very well and provide good predictive accuracy, in high-yielding (Chiew et al., 1993) and low yielding catchments (Ye et al., 1996). The conceptual models STANFORD IV (Crawford and Linsley, 1966) and SACRAMENTO (Burnash et al., 1973) should be mentioned here because they were perhaps the most popular in worldwide applications. A review of achievements in conceptual modelling is provided by Clarke (1973), Ward (1967), Gray (1973) and Anderson and Burt (1985).

The IHACRES model, applied in the present study, is a hybrid metric-conceptual model based in part on the Instantaneous Unit Hydrograph (IUH) technique. This method represents total streamflow response as a linear convolution of the IUH (hydrograph of runoff resulting from one unit of effective rainfall generated uniformly over a catchment area with instantaneous duration) with rainfall excess or effective rainfall. It is partly metric in the sense that measured precipitation-discharge observations are used to infer the configuration and number of stores used to represent the linear convolution. According to Chow (1964), the idea of the applying the IUH technique for the conceptual modelling of catchment runoff first appeared in the Report of the Committee on Floods (1930). Clark (1945) adapted this method for hydrograph analysis. Cuenod (1956) applied a reverse process of numerical convolution in order to compute the outflow hydrograph using long time series of streamflow
data. In his book Chow (1964) lists references to key publications contributing new achievements to the IUH conceptual approach during the 1950s and 1960s.

A detailed review of modern methods in hydrological modelling is provided by Jayatilaka and Connell (1995). Two types of models were considered in this review. Following the classification of Wheater et al. (1993) they are: (1) physically based distributed models: SHE (European Hydrology System, described in Abbott et al., 1986), TOPOG (Dawes and Short, 1994), IHDM (Institute of Hydrology Distributed Model; Beven et al., 1987), THALES (Grayson et al., 1992), TOPMODEL (Beven and Kirkby, 1979; Beven et al., 1984), WSHS (Watershed Hydrologic System), (Al-Soufi 1987, 1989) and (2) lumped conceptual models: SDI (Kuczera, 1988), CATPRO (Kuczera et al., 1993) and MIDASS (Nathan, 1993).

General conclusions provided by Jayatilaka and Connell (1995) correspond well with our choice of the conceptual model as a tool for catchment runoff modelling in the selected region. They emphasise that the advantage of the conceptual models is their ability to predict spatially average streamflow response. Therefore, models of this type are suitable in circumstances with lack of spatially distributed catchment input. Being structurally simpler than physically-based models, the conceptual models require long records of hydrological data for calibration and simulation. The region of the south-eastern Basins of the MDDD, chosen for consideration here, satisfies these requirements because it has been instrumented for a relatively long period. Streamflow, precipitation and temperature data are available for decades in the majority of gauging sites in this region.

Some disadvantages of the physically-based models are mentioned by Jayatilaka and Connell (1995). Models of this kind are usually designed "to utilise parameters that have physical meaning. This implies that the model parameters can be estimated through independent measurements. For accurate calibration, considerable care is required to ensure that a
unique optimal parameter set is obtained and that the physical basis of the process representations is not obscure. It is not possible to satisfy such requirements when modelling of surface runoff to be implemented here is so comprehensive (total area over 13,000 km²).

Thus, conceptual lumped rainfall-runoff models seem to be the most adequate type of model for the streamflow analysis required in the region selected and for the particular purposes of this study. The model IHACRES falls sufficiently well within this class of models, and its number of parameters (six) to be fitted is small compared with other conceptual models, yet its performance has been impressive across a range of hydroclimatologies (e.g., Jakeman and Hornberger, 1993).

Other significant arguments for the use of conceptual hydrological models are provided by Todini (1996) and Jakeman et al. (1992). Todini (1996) emphasises that models of this type allow one to link together process components reflecting physical concepts, under the presumption that model parameters have physical meaning. It allows one to establish their parameter values without reference to the observed streamflow data. This means that parameters of conceptual models could be defined from physiographic characteristics (landscape, vegetation cover, etc.) of the catchment where they are applied. This is another one of the important reasons why the IHACRES model was selected as a tool for comprehensive analysis of the hydrological regime at the Basin scale. Following arguments in Jakeman et al. (1992), useful results in applying IHACRES to ungauged catchments were obtained by Post et al. (1996), Post and Jakeman (1996), Sefton et al. (1993) and Sefton and Boorman (1996), where relationships between the IHACRES model parameters and catchment descriptors were established. This problem is discussed in more detail in Chapter 3.

An assumption related to the analysis presented here is that vegetation cover in the region remains stable. Thus changes in the cover due to human interference or elevated carbon
dioxide influence on plant transpiration are neglected. However, in future work, it is possible to analyse the IHACRES parameter values, already estimated through time in this thesis, to attempt identification of their relationship with vegetation cover and other physiographic descriptors. The background to this is discussed in Section 1.5.

1.3.2. Recent advances in surface runoff modelling

Hornberger and Boyer (1995) reviewed over a hundred articles reflecting recent advances in hydrological modelling. Several recent achievements in this area are related to advances in information technology. Much of the recent progress of hydrological modelling is connected to new methods of spatial data measurement, improvement in their quality and new methods of spatial interpolation techniques. Traditionally, the problem of spatial variability was handled in hydrology by dividing a catchment into a set of smaller areal units where climatological and geomorphological properties could be considered as homogeneous. One of the possible answers to the question of how far this process of division can go may involve use of the modern concept of Representative Elementary Area (Wood et al., 1988, 1990; Bloeschl et al., 1995). The Representative Elementary Area is the smallest area (of order 1 km$^2$ under some conditions) for which the pattern of inner heterogeneity is relatively negligible under certain conditions. It remains, however, an unsolved problem in catchment hydrology and a matter of active research as to how to apply the model parameter values estimated from one scale to another.

The use of digital terrain data is one facility sought to improve the quality of hydrological modelling. Two models, which use the linkage between hydrological methods and modern computer graphic techniques, should be mentioned. These are TOPMODEL (Beven and Kirkby, 1979; Beven et al., 1984) and TOPOG (Dawes and Short, 1994). The use of remotely sensed data is also an important source of improvement of hydrological model
validation. The SWRRB (Simulator for Water Resources in Rural Basins) model was applied using radar information which provided accurate rainfall input over the whole catchment (Nicks and Scheibe, 1992). Kite and Kouwen (1992) used a land cover classification to improve performance of the SLURP (Simple Lumped Reservoir Parametric) model. Some results of remotely sensed data applications to snow melt/accumulation models are reviewed in the Introduction to Chapter 4 of this thesis.

The use of chemical data is also a very important tool used to seek advances in understanding and modelling of response. New achievements in hydrochemical modelling are out of the scope of this review. It should be emphasised however that the use of chemical data to improve understanding of surface runoff itself is important. Chemical data are used, for instance, for separation of ‘soil water’, ‘storm water’ and ‘ground water’ in surface runoff. Hornberger and Boyer (1995) note that the tracing of "unique chemical signature" can support differentiation of these components in stream runoff (Christofersen et al., 1990; De Grosbois et al., 1988; Stewart and McDonnell, 1991).

Two serious problems of streamflow modelling were mentioned by Hornberger and Boyer (1995). These are: (1) identification of model parameters and (2) incorporation of relatively small-scale heterogeneity into a model applied on a larger scale. Both of these problems are discussed in the present work in the context of the IHACRES model application for streamflow modelling up to the Basin scale. The importance of systematic studies of the potential relationships between measurable catchment attributes and model parameters has been emphasised as a major future direction in hydrological modelling (eg Jakeman et al., 1992).

Scaling issues in hydrology and the structuring of modern approaches in hydrology are discussed by Bloeschl and Sivapalan (1995). They define some basic terms, such as ‘process
scale', 'observation scale' and 'modelling (working) scale'. The division of existing models into 'predictive' and 'investigative' models is suggested. They propose structuring the conceptual modelling process for both types of models into five steps: (a) collecting and analysing data, (b) developing a conceptual model which describes the hydrological characteristics of a catchment, (c) translating the conceptual model into a mathematical model, (d) calibrating the mathematical model to fit a part of the historical records and (e) validating (in this work we use the term 'simulation') the model against long term historical data sets (Mackey and Riley, 1991; O'Connell, 1991). This structure has been adopted in the present research.

The term scale is defined by Bloeschl and Sivapalan (1995) as a characteristic time or distance of a process, observation or model. The process of information transfer from one scale to another (for instance, using large scale data and models for small-scale predictions) is defined as scaling. Review papers dealing with scaling issues in hydrology include Beven (1991), Dooge (1982, 1986), Dozier (1992), Gupta et al. (1986), Klemes (1983) and Wood et al. (1990). A classification of hydrological processes according to their typical time and length is also provided in Bloeschl and Sivapalan (1995). This classification takes into consideration a range of scales: from minutes (flashflood) to hundreds of years (aquifer flow) in time and from 1 meter soil profiles to thousand kilometre river floods in space. The nature of heterogeneity and variability in space and time, as well as linkage across scales, is discussed in their work.

Bloeschl and Sivapalan (1995) emphasise the rapid development of new dimensional techniques in hydrology. They were used often in hydraulic applications but relatively rarely applied in catchment hydrology. A classification of such techniques is suggested: dimensional analysis, similarity analysis and functional normalisation (i.e. establishing empirical
relationships between catchment variables). The concept of similarity serves as a basis for all of these methods. A similarity between two systems exists when characteristics of one system can be transferred to those of another one by a simple conversion or scale factor (Langhaar, 1951). When the Instantaneous Unit Hydrograph of two catchments are related by a constant scale factor they are called kinematically similar. One example of a model used to examine such similarity is the geomorphologic unit hydrograph (Gupta et al., 1980; Rodrigues-Itrube and Valdes, 1979; Rodrigues-Itrube et al., 1979). Dimensional and similarity analysis techniques are developing rapidly (Rodrigues-Itrube et al., 1992).

Another recent development in hydrological modelling is the semi-distributed conceptual rainfall-runoff model, such as ARNO (Todini, 1996). ARNO is being used in land-surface-atmosphere processes research and for operational flood forecasting in different countries, for example, in Italy, China and Germany. The ARNO model has two main components: a soil moisture balance module, and a runoff transfer module describing routing of streamflow to the outlet of a catchment. Additional component modules representing evapotranspiration, snow melt/accumulation and groundwater processes are also incorporated in the ARNO model. This model has also been used for estimating climate change impacts by coupling with the ECHAM General Circulation Model (Todini, 1996).

A discussion of appropriate criteria for assessment of hydrological models is provided by ASCE (1993). The report addresses the problem of estimating model quality from the point of view of practical applicability. Some basic recommendations on particular statistical measures are provided. The Nash-Sutcliffe efficiency coefficient (Nash and Sutcliffe, 1970) and the deviation of runoff volume (Martinec and Rango, 1989) recommended in the report are widely used in this study for quantification of model performance.
1.3.3. Review of IHACRES applications

Another important reason supporting selection of IHACRES as a modelling tool is that it has been tested worldwide for catchments of different sizes and under different climatic conditions. Jakeman et al. (1990) first used the IHACRES model for modelling streamflow in two small upland catchments in Wales, with area 0.34 km$^2$ for the CI5 catchment and 0.72 km$^2$ for the CI6 catchment. An hourly timestep was used in this work. Jakeman and Hornberger (1993) applied the IHACRES model to catchments ranging in area from 490 m$^2$ (the small experimental catchment Hydrohill in China) to 89.6 km$^2$ (Orroral Valley in the Australian Capital Territory). The model identification was performed on a daily timestep, except for the Hydrohill catchment, where a 6 minute time-step was applied. The climatic conditions varied from 950 mm of mean annual precipitation in the Hydrohill area to 2953 mm for the Monachyle and 2795 mm for the Kirkton Rivers in Scotland. Two small American catchments (Watershed 34 and 36, Coweeta, North Carolina) were also analysed successfully in their paper. Successful calibration of IHACRES was obtained for several ephemeral rivers: the Bass River catchment in Southern Victoria (Ye et al., 1995a), the Orara River catchment in northern New South Wales (Ye et al., 1995b) and the Sugarloaf Creek catchment in the Goulburn Basin of the MDDD (Schreider et al., 1996a, Chapter 2 of this thesis). The large catchments of the Teifi River in Wales (894 km$^2$), the French Board River in North Carolina (767 km$^2$) and the Exe River at Thorverton (601 km$^2$) were successfully modelled by Jakeman et al. (1993).

Post and Jakeman (1996) calibrated and used the IHACRES model parameters as an indicator of vegetation changes for the 17 small mountain ash catchments in the Maroondah region of Victoria, near Melbourne. Catchments ranged from 0.04 km$^2$ to 0.65 km$^2$ in size. Another example of an IHACRES application is the 490 km$^2$ Queanbeyan River
catchment at Tinderry, in the Australian Capital Territory (Schreider et al., 1995a). Hansen et al. (1995) applied the model using a 6 minute time step for two experimental catchments in China (Hydrohill and Chuzhou).

A comparative analysis of IHACRES performance with two other conceptual models was implemented by Ye et al. (1996). Three catchments, the Salmon (0.82 km²), Stones (15 km²) and Canning (517 km²) Rivers in Western Australia were considered, to analyse the performance of IHACRES, LASCAM (Sivapalan et al., 1996a, 1996b, 1996c) and GSFB (Boughton, 1984) models. Results obtained with IHACRES were competitive with those obtained by other models for the daily time step as well as for a monthly time step approach. However, the number of parameters of the IHACRES model (6) is less than in the models selected for comparative analysis: GSFB (8), LASCAM (22).

1.4. The climate change impact problem

The question addressed here is why is the prediction of climate change impacts important? An answer can be found for instance in Pittock (1995), where the socioeconomic aspects of possible climate impacts are discussed. He emphasises:

(a) coastal impacts, related to elevation of sea level, due to the global warming effect, which is estimated by some experts between 15 and 95 cm at 2100 (Wigley, 1995);

(b) a world food security problem, related to changes in optimal temperature levels for some major world crops, increasing drought frequency and soil erosion levels; and

(c) disasters, health and loss of life, related to increasing floods and intense rainfall events, disruptions of water supply in some regions and increase of diseases induced by high temperature levels.
Other impact issues are also important. For example, the impact on biodiversity seems to be very plausible, because of the translation of ecological niches due to changes in climate and the surface water regime. Several species may even become extinct such as the mountain pygmy-possum whose habitat in the Australian Alpine region is very vulnerable to possible climate change (Mansergh and Broom, 1994).

1.5. Fast track and long term methodologies for predicting catchment hydrologic response

Two approaches for assessment of either large scale hydrologic impacts or for climate/earth system modelling have been proposed by Jakeman et al. (1995): fast track and long term approaches. The strategy of the fast track approach, which is applied in the present work, is to parameterise relationships directly between incident climate and evapotranspiration/runoff using a conceptual rainfall-runoff model and daily climatic and streamflow time series. With a simple conceptual model like IHACRES, there is now the capability to undertake this rapidly and accurately, at spatial scales greater than or equal to those determined by the availability of discharge data. In many areas, major headwater catchments (with areas ranging from hundreds to thousands km²) have at least a few years of daily discharge records. For climate or earth system models requiring a description of land surface-atmosphere energy and water interactions, additional work to that for hydrologic impact assessment is required. Thus it is necessary to spatially disaggregate climate forcing variables from the grid scale down to the relevant catchment scale. It is also required to temporally disaggregate daily evapotranspiration and energy feedbacks from the land surface to the atmosphere down to a time step of the order of an hour.

In this fast track approach, parameterisation of all gauged catchments can be undertaken off-line and, once parameterisations are inserted in a climate model, simulation of the interactions
involves low computational demands. These parameterisations are then valid at least for historically-tested climate conditions, vegetation and land use status. Such an approach is useful for improving simulation under present time climate conditions because the land surface-atmosphere energy and water interactions can be represented very accurately, allowing climate/earth system modellers to attend to errors elsewhere in their models and to develop improved representations of other components of their system. Whether it be for climate models, impact models, or carbon cycle studies, changes in land cover and plant water use efficiency can only be handled empirically at present by making known directional changes in the conceptual hydrological model parameters associated with these processes. More precise estimates of the magnitude of these changes is expected as understanding accrues from the long term approach which is discussed next.

The long term approach allows one to develop the capability to represent variability in land cover and the associated variability in hydrologic response for large scale impact assessment or climate and earth system modelling, or to predict a water balance in ungauged catchments. In this case the areas considered must be decomposed into ‘small’ catchments of appropriate size. This decomposition will depend upon many factors but could be as small as several km² for headwater catchments. From small catchments with gauged discharge data, relationships need to be constructed between hydrologic response characteristics (or model’s parameters) and physical catchment descriptors. These relationships are intended to permit the simulation of sub-daily streamflow and evapotranspiration for stipulated changes in land use and for ungauged catchments compromising a region. Successful results of establishing such relationships were obtained in Post and Jakeman (1996), Post et al. (1996), Sefton and Boorman (1996), and Sefton et al., (1993). It is intended that the parameters of the
IHACRES model estimated for the present study region will be used to investigate their relationships to physical catchment descriptors.

1.6. Simplifications of the modelling approach

In the present work, the model identification and estimation of possible climate impacts on streamflow were implemented in four Basins with a large total area over 13,000 km². Following the concept stated by Barnes (1993) that "modelling effort should be balanced, with effort in proportion to the original purpose of the model", the snow-free catchments of the Goulburn and Ovens Basins (Chapter 2) were modelled using input precipitation data from single stations only. The results of the model identification might be slightly improved if more complicated areal rainfall estimation techniques were used, such as some spatially interpolated precipitation, as was necessary for the snow-affected catchments (Chapter 4). This analysis was not implemented for the snow-free catchments. The preference was to model a larger number of catchments than to model a smaller number with slightly higher quality.

A scaling issue examined in the thesis was the problem of how large catchments selected for modelling can be. The experiment with a composite catchment in the Goulburn Basin (Section 2.5.2) shows that a catchment with an area of about 2,500 km² can be modelled with almost the same quality as its components with areas of some hundreds of km². The model fit to the integral streamflow of the five rivers in the composite catchment provided a similar result to the sum of the five individually modelled streamflows. This allows a fivefold reduction in the number of free parameters and an associated reduction in calibration effort. In subsequent analysis of the Upper Murray Basin, these results were used as motivation to successfully test larger scale streamflow modelling than was initially considered, in the Tooma (1819 km²), Mitta-Mitta (1533 km²) and Upper Murray (1165 km²) catchments. It was not
necessary to subdivide these catchments into minor subcatchments to obtain good predictions of daily flow (Chapters 5 and 6).

Another limitation of the approach applied in the present work is related to the assumption that the overall vegetation response to a given precipitation and temperature input will remain similar for the periods (2030 and 2070) when the climatic impacts on streamflow are assessed. However, the vegetation cover and/or its evapotranspiration response may change with future changes in climatic patterns of temperature, precipitation, net radiation and fertilisation effects related to increases in carbon dioxide.

The impacts of climate vegetation structure worldwide was considered in Monserud et al. (1993). Climate scenarios based on four GCMs were applied to the entire globe subdivided into gridcells with resolution 0.5 x 0.5. A modified version of Budyko's vegetation model was applied in order to calculate the ratio of annual pan evaporation to the annual precipitation for every gridcell. The methodology accepted by Monserud et al. (1993) implies that this ratio is a major factor determining boundaries between vegetation zones. They conclude that boreal and temperate vegetation zones are predicted to undergo the maximum changes. In particularly, all boreal zones are predicted to shrink. The classes of vegetation located closest to the polar zones (or located highest in mountains) are expected to be partially replaced by their neighbouring vegetation classes that are typical of more temperate climatic zones.

This general conclusion is supported by Busby (1988) who analysed possible climatic impacts on Australian vegetation cover and found that elevation of tree-lines in the Alpine regions of Victoria and Tasmania are expected to increase. A methodology for estimating possible climate changes in Australia's terrestrial ecosystems is developed in Williams et al. (1994). It is based on the analysis of correlations between present vegetation areal distribution and climatic factors at these sites and, subsequent extrapolation of these relationships for future climatic
changes. The strategy formulated is very sophisticated, taking into account many factors including conservation implications and land use changes, and has not yet been implemented.

As well as the climatic factors, human-induced factors, such as deforestation and natural hazards like bush fires, also have the potential to severely affect vegetation cover and response in the area considered. Land use changes in the rural areas where the analysis was implemented can be neglected because the area modelled is located mostly in the upper alpine areas of all four Basins. Analysis of this problem in Australian regions is provided by Kirkpatrick (1994). Emphasised in this book is the relatively small loss in the vegetation of Australia's alpine regions, compared with other flora communities.

In summary, from the above brief analysis of possible alterations in vegetation under climate change or induced by human activities, two points should be mentioned. Firstly, boreal flora tend to be replaced by temperate types. In the catchments considered, this means increases in the elevation of the alpine tree-line and the line between Alpine ashes and snow gums. While the total forested area of the catchments considered should therefore increase in the long term, the periods over which climate impacts are estimated in this thesis are too short (about 70 years) for forests to grow over considerable areas. Secondly, deforestation due to logging is also unlikely in these areas because most parts of this region are governmentally protected reserves, while the effects of any bush fires are likely to be either spatially restricted or short term in nature. Thus the assumption, that overall vegetation response will remain similar to that over recent history for the periods when the possible climatic impacts on streamflow were analysed, seems to be quite plausible.

Another unknown which will need further attention in the future as improved knowledge becomes available is the hydrologic effect increases, reducing plant water use. The closure is of leaf growth, and this can offset the reduction of elevated carbon dioxide levels. Plant
stomata close as carbon dioxide often accompanied by carbon dioxide enhancement in water loss. Given that no one seems to have been able to discern this effect from water balance analysis in catchments over the last 50 years or so, when there have been appreciable changes in atmospheric carbon dioxide changes, it is probable that this is a second order effect for the next 70 years (depending ultimately of course on the level of emissions realised), buried as it were in the noise of precipitation - streamflow observation and model errors.

CATCHMENT TO BASIN SCALE: THE GOULBURN AND OVEN BASINS

Summary

A rainfall-runoff model with hydrograph separation is applied on a daily-time step to a large upland area of the case of Warrandyte. Simulated flow and parameters in the case of the Goulburn and Ovens basins. This is the first application and testing of the model on such a basin, involving two basins where the total drainage area of the catchments examined is about 17 000 km². The model also represents the first evaluation of a rainfall-runoff model at large basin scale, which is comprehensive in terms of the number of catchments investigated and the number of calibration and simulation periods used. The model was tested by streamflow over the entire record period of observation for the catchments under consideration. The results show that the model closely duplicates the observed streamflow.
CHAPTER 2

MODELLING RAINFALL-RUNOFF FROM LARGE CATCHMENT TO BASIN SCALE: THE GOULBURN AND Ovens BASINS

Summary

A rainfall-runoff model (IHACRES) is applied on a daily timestep to a large upland area of the state of Victoria, Australia. Successful calibrations of this dynamic lumped parameter model were performed for 12 rivers of the Goulburn Basin and 5 rivers contributing streamflow to the Ovens Basin. This is the first application and testing of the model on such a scale, involving two Basins where the total drainage area of the catchments modelled is about 6,500 km². This work also represents the first evaluation of a rainfall-runoff model at large catchment scale, which is comprehensive in terms of the number of catchments investigated and the number of calibration and simulation periods used. The models were tested by simulation over the entire common period of observation for the catchments under consideration. The results show that the models closely simulate the observed streamflow.
Simulation tests are used to select the best models for each catchment. This allows simulation of the water regime during long historical (approximately 90 year) periods when only climatological (rainfall and temperature) data were available. The procedure is extremely important for subsequence estimation of the effect of climate variability and of the possible impact of climate change on the hydrologic regime in the region and, in particular, for supporting irrigation management of the Basin.

Analysis of a composite catchment (2,417 km²) and its five separate subcatchments indicates that the information content in rainfall-streamflow data is independent of catchment size. Dynamic modelling of the daily water balance at macroscale is limited principally by the adequacy of the precipitation gauging network. When a good estimate of areal precipitation is available, it is not necessary to consider subcatchment-scale variability for modelling in these catchments if one is only interested in daily discharge and evaporation losses from the catchments. The climate throughout the Murray Basin is humid and the mean annual value of precipitation is about 300 mm, whereas in the south-eastern part of the Murray-Darling Basin belonging to the state of Victoria is humid and fertile, and is one of the most important parts of the Basin for rural industry (see Water Victoria: A Resource Handbook, 1989).

2.1. Introduction

The Murray River with its tributaries is the largest river system in Australia. The rivers of this system constitute the so-called Murray-Darling Drainage Division (MDDD). The total area of this division is over one million square kilometres or approximately one-seventh the area of Australia. A detailed description of climatic conditions and water resources in this region is available in Nix and Kalma (1982) and Fleming (1982).
The Goulburn and Ovens Basins (Basins N 5 and N 3, respectively) of the Murray-Darling Drainage Division (see Figure 2.1a, b) were selected as the initial case study to model streamflow in Australia at Basin scale. The main argument for such a choice is the importance of the Murray-Darling Irrigation District for Australian rural industry and the importance of the Goulburn Basin for irrigation supply within this District. The Ovens Basin is also an important contributor to irrigation in region selected.

2.2. Goulburn Basin Description

The Basin covers more than 16,000 km² in the central part of Victoria and extends from the Great Dividing Range in the Victorian Alps in its south-eastern part to the Murray River in the north-west. The total mean annual discharge of the Goulburn River is over 3,000,000 ML.

Climatology and physiography vary throughout the Goulburn Basin. In the western part, the mean annual value of precipitation is about 500 mm, whereas in the south-eastern part near the Great Dividing Range the climate is much more humid and the mean annual value of precipitation reaches 1500 mm. The distribution of vegetation ranges from forested areas in the south-east to agricultural regions in the west. The most common soils in this Basin are *alpine humic soils* on well drained hillslopes and *acid peats* on poorly drained slopes and in valley bottoms (Walker *et al.*, 1983). Agriculture in the Goulburn Basin is very diverse, varying from logging in its south-east part to beef and dairy cattle production and fruit plantations in its northern part.
GOULBURN BASIN: MAJOR RIVERS AND GAUGING STATIONS FOR IRRIGATION SUPPLY

Figure 2.1a. River network, meteorological and discharge stations for the catchments under consideration in the Goulburn Basin
Figure 2.1b. River network, meteorological and discharge stations for the catchments under consideration in the Ovens Basin
Total water use in the Basin is about 780,000 ML per year, almost entirely for irrigation. The majority of this water is withdrawn from the Basin's surface water resources. Only about 10,000 ML are drawn from groundwater. The Goulburn Basin accounts for approximately 40% of total irrigation water use in Victoria. About half of this amount (740,000 ML per year) is used for irrigation needs within the Basin while the other half is exported to the Loddon, Campaspe and Broken River Basins.

Lake Eildon, the second largest reservoir in Victoria, is located in the south-eastern part of this Basin (Figure 2.1a). The rivers which flow into it are the Big, Upper Goulburn, Jamieson, Howqua and Delatite. Downstream of this lake, the Goulburn River flows in a westerly direction. The major tributaries downstream of this lake are the Rubicon, Acheron and Yea Rivers which flow from the northern slopes of the Victorian Alps. Near the junction with Sugarloaf Creek the Goulburn River changes direction and swings to the north until its junction with the Murray River.

We selected 12 catchments in the Basin in order to consider all rivers contributing substantial water to the main stream of the Goulburn River. These catchments are listed in Tables 2.1 and 2.2 and shown in Figure 2.1a (Victorian Surface Water Information, 1984). They are divided into two groups: rivers upstream of Lake Eildon, and rivers entering the Goulburn River downstream of the Lake.

The longest records of surface air temperature taken in the upper part of the Basin are for Lake Eildon meteorological station 88023 (Figure 2.1a). We used these temperature data for all catchments considered. Best model performance for the catchments upstream of Lake Eildon was obtained with precipitation data recorded at Jamieson Post Office (station 83017).
Table 2.1. The catchments upstream of Lake Eildon (Victorian Surface Water Information, 1984)

<table>
<thead>
<tr>
<th>Station number</th>
<th>River and station location</th>
<th>Mean annual discharge (ML)</th>
<th>Area (km²)</th>
<th>Commencement of continuous streamflow records</th>
</tr>
</thead>
<tbody>
<tr>
<td>405219</td>
<td>Goulburn River at Dohertys</td>
<td>394,000</td>
<td>694</td>
<td>1954</td>
</tr>
<tr>
<td>405227</td>
<td>Big River at Jamieson</td>
<td>330,000</td>
<td>619</td>
<td>1957</td>
</tr>
<tr>
<td>405218</td>
<td>Jamieson River at Gerrans Bridge</td>
<td>246,000</td>
<td>368</td>
<td>1954</td>
</tr>
<tr>
<td>405215</td>
<td>Howqua River at Glen Esk</td>
<td>200,000</td>
<td>368</td>
<td>1973</td>
</tr>
<tr>
<td>405214</td>
<td>Delatite River at Tonga Bridge</td>
<td>131,000</td>
<td>368</td>
<td>1947</td>
</tr>
<tr>
<td>405251</td>
<td>Braneeet Creek at Ankona</td>
<td>18,900</td>
<td>122</td>
<td>1971</td>
</tr>
</tbody>
</table>

Table 2.2. The catchments downstream of Lake Eildon (Victorian Surface Water Information, 1984)

<table>
<thead>
<tr>
<th>Station number</th>
<th>River and station location</th>
<th>Mean annual discharge (ML)</th>
<th>Area (km²)</th>
<th>Commencement of continuous streamflow records</th>
</tr>
</thead>
<tbody>
<tr>
<td>405241</td>
<td>Rubicon River at Rubicon</td>
<td>138,000</td>
<td>129</td>
<td>1949</td>
</tr>
<tr>
<td>405209</td>
<td>Acheron River at Taggerty</td>
<td>337,000</td>
<td>619</td>
<td>1945</td>
</tr>
<tr>
<td>405205</td>
<td>Murrindindi River above &quot;Colwels&quot;</td>
<td>59,000</td>
<td>101</td>
<td>1939</td>
</tr>
<tr>
<td>405217</td>
<td>Yea River at Delvins Bridge</td>
<td>113,000</td>
<td>360</td>
<td>1954</td>
</tr>
<tr>
<td>405231</td>
<td>King Parrot Creek at Flower Dale</td>
<td>35,200</td>
<td>184</td>
<td>1961</td>
</tr>
<tr>
<td>405240</td>
<td>Sugarloaf Creek at Ash Bridge</td>
<td>66,800</td>
<td>609</td>
<td>1963</td>
</tr>
</tbody>
</table>
All these catchments were calibrated with the precipitation time series from this station. The pattern of precipitation measured at Jamieson station is similar to the spatial mean rainfall for this part of the Basin. Acheron meterological station (88000) has been used for modelling the Acheron River, Rubicon station (88068) for the Rubicon River, Glenburn station (88028) for the Murrindindi and Yea Rivers, Wallaby Creek weir station (88060) for the King Parrot River and Seymour station (88053) for Sugarloaf Creek.

2.3. The Description of the Ovens Basins

2.3.1 Water resources and physiography

The Ovens River (Figure 2.1b) flows from the northern slopes of the Victorian Alps in a north-westerly direction until its junction with the Murray River near Lake Mulwala. The total area of the Basin covers more than 7,770 km², compared to more than 16,000 km² for the Goulburn Basin. The total mean annual discharge of the Ovens River is over 1,600,000 ML which constitutes more than half of the total discharge of the Goulburn Basin and 7.3% of the total discharge of the state of Victoria.

Lakes Buffalo (24,000 ML capacity) and William Hovell (13,500 ML capacity) are the two major artificial reservoirs in the Basin located on the two main tributaries of the Ovens River: the Buffalo River and the King River (mean annual discharge at the sites of gauging stations 403222 and 403227 are 178,000 ML and 261,000 ML, respectively, see Table 2.7). The capacity of these reservoirs is relatively small compared with the total annual discharge of the rivers. The effect of artificial regulation on streamflow downstream of these lakes can be neglected even during the summer periods. The King River is a tributary of the Ovens River with a mean annual discharge of more than 400,000 ML at its junction with the Ovens near
the city of Wangaratta (streamflow gauging station N 403201). The Buffalo River is the biggest tributary of the Ovens with a mean annual discharge of about 500,000 ML (Buffalo River at Smith suspension bridge, station N 403207). It joins the Ovens downstream of the town of Myrtleford. The Buffalo River itself has two large tributaries which are the Rose and Dandongadale Rivers. Rose River streamflow is not recorded continuously and is therefore excluded from our analysis. The other major tributary of the Ovens River is the Buckland River joining it downstream of the town of Bright.

The climatology and physiography of the Ovens Basin are less heterogeneous than that of the Goulburn Basin. The mean annual value of precipitation is more than 1500 mm in its highest part near the Great Dividing Ridge (1500 mm near Mt Hotham and over 1800 mm at Mt Buffalo). The central part of the Basin also receives relatively high rainfall (900 mm at Myrtleford in the central eastern part of the Basin and about 1000 mm near Lake William Hovell at the west of the Basin). The mean level of precipitation recorded in its north-east part near Wangaratta is 635 mm per year. Sixty five percent of precipitation in the Basin occurs during the winter, while the summer is warm and dry (Water Victoria: A Resource Handbook, 1989).

Tobacco is the most economically significant crop in the Ovens Basin, which provides three-quarters of the tobacco grown in Victoria. Other important agricultural products in this valley are livestock production, sheep, beef cattle and dairying. Total average water use in the Basin is about 30,000 ML per year, 64 percent of which is diverted from the Ovens River and its tributaries. A major part of this water use is irrigation which constitutes more than 16,000 ML annually. This amount is relatively small compared with approximately 740,000 ML used
annually for irrigation in the Goulburn Basin. About the same amount, around 700,000 ML, is
annually withdrawn from this Basin to the Loddon, Campaspe and Broken Rivers Basins also
for irrigation use. Much of the outflow from both the Ovens and Goulburn Rivers into the
Murray is used further downstream for irrigation.

The distribution of vegetation in the Ovens Basin is similar to the Goulburn Basin, ranging
from forested zones in the highland areas to agricultural regions in the south-west. The soils
in this Basin are also similar to those of the Goulburn Basin: alpine humic soils on well
drained hillslopes and acid peats on poorly drained slopes and in valley bottoms (Walker et
al, 1983).

2.3.2. Climatological data of the Ovens Basin

The longest records of surface air temperature taken in the upper part of the Basin are for
Bright Shire Council meteorological station 83067 (Figure 2.1b), available from 1969. Daily
temperature calculated as the mean arithmetic value of daily maximum and daily minimum
temperature was used in the analysis. These temperature data were used for all catchments
considered. The best model performance for the catchments of the Upper Ovens (403205),
Buckland (403233), Buffalo (403222) and Dandongadale (403218) Rivers was obtained with
precipitation data recorded at Mt. Buffalo (station 83073). The Whitfield station (83031) was
used for modelling the King River at Cheshunt (403227).

2.4. The IHACRES model

The lumped parameter rainfall-runoff model IHACRES used here has been tested successfully
in several regions worldwide for catchments of different sizes and under different climate
conditions (eg. Jakeman and Hornberger, 1993; Jakeman et al., 1993; Ye et al., 1995a; Schreider et al., 1995a; Post et al., 1996). It has been calibrated and evaluated comprehensively on two large catchments to date - the French Broad River in North Carolina and the Teifi River in Wales (Jakeman et al., 1993).

The IHACRES model was first described in Jakeman et al. (1990), and its loss module was updated by Jakeman and Hornberger (1993). The model has two modules. A non-linear loss module which at each timestep \( k \) (a daily timestep is taken in this work) transforms measured rainfall \( r_k \) into effective rainfall \( u_k \) using temperature or pan evaporation data \( t_k \). A linear module then describes the travel of effective rainfall to streamflow \( y_k \) on the basis of a total unit hydrograph approximation. The latter module invokes a recursive relation at time step \( k \) for modelled streamflow \( y_k \) computed as a linear combination of its past values and current and past effective rainfall.

The non-linear loss module is used to account for the effect of antecedent weather conditions on the current status \( s_k \) of soil moisture and vegetation conditions, and for evapotranspiration effects. Here the effective rainfall \( u_k \) is calculated from the measured rainfall \( r_k \) and temperature \( t_k \) in the catchment area by the formulae:

\[
\begin{align*}
    u_k &= r_k (s_k + s_{k-1}) / 2 \\
    s_k &= r_k / c + (1 - 1/\tau_w(t_k)) s_{k-1} \\
    \tau_w(t_k) &= \tau_w \exp(20f - t_kf)
\end{align*}
\]

The constant \( c \) is calculated so that the volume of effective rainfall is equal to the total streamflow for the calibration period. \( \tau_w \) and \( f \) are parameters to be optimised: \( \tau_w \) is a time
constant reflecting the rate of drying (in days) of the catchment at 20°C and $f$ is a factor which modulates this rate as temperature varies.

The linear module identified as most appropriate in this work for the Goulburn catchments, and for most humid catchments (see Jakeman and Hornberger, 1993) is

$$y_k = -a_1 y_{k-1} - a_2 y_{k-2} + b_0 u_k + b_1 u_{k-1}$$  \hspace{1cm} (2.2)

It implies that the effective rainfall is considered to travel through two parallel stores. This means that during dry periods the recession of streamflow is a superposition of two exponential decay functions, one of them being responsible for quick recession and the other for recession of the slow component. The exponential functions are defined by parameters such as the quick and slow store time constants ($\tau_q$ and $\tau_i$) and relative volumetric throughput ($\nu_q = 1 - \nu_i$) of the quick and slow components. The parameters $\tau_w$, $f$, $c$, $\tau_i$, $\tau_q$ and $\nu_q$ have been called dynamic response characteristics (DRCs) of the catchment and the latter three are functions of the $a_1$, $a_2$, $b_0$, $b_1$ coefficients in the linear equation (2.2). Jakeman et al. (1990) show how to calculate from (2.2) the parameters $\tau_q$, $\tau_i$ and $\nu_q$, as well as a total unit hydrograph and its quick and slow components. The total unit hydrograph is the streamflow response of the streamflow to an initial unit pulse of effective rainfall over one timestep.

2.5. Model performance in the Goulburn Basin and catchment response profiles

2.5.1. Upstream catchments

Model calibration was performed using the daily precipitation-temperature-streamflow time series during the common period of observation, 1975-1990, years when records for all stations were available. This period was divided into 13 two-year calibration periods (CP),
each with one year overlapping the adjacent CP. From 8 (Blanket Creek) to 13 (Howqua River) two-year CP models were successfully calibrated for each of these catchments. For some two-year periods, models could not be calibrated because of instability of $a$-values in equation (2.2). The calibration results, in terms of model efficiency, are summarised in Table 2.3. The model fit to the observed flow for one of the calibration periods is shown in Figure 2.2. This is a challenging period to fit because it includes a normal and a drought year. The model efficiency statistic $E$, or proportion of observed stream discharge variance explained by the model, is defined as

$$E = 1 - \frac{\sum(y_i - y'i)^2}{\sum(y_i - y_{mean})^2},$$

where $y_i$ denotes observed flow, $y'i$ is modelled flow and $y_{mean}$ is mean observed flow (Nash and Satcliff, 1970). The high values of $E$ illustrate the performance of these models in explaining the variance of observed streamflow. The calibration results are considered successful if the efficiency coefficient exceed 0.7, while for simulation over long periods a value of $E > 0.6$ is considered acceptable. The poor performance of the model for some CP's is related to the fact that insufficient information in precipitation and discharge time series is available for identification of all model parameters. Mathematically, it means that the information matrix calculated during the calibration procedure for the linear module parameters is not invertible.

Figure 2.3 shows the catchment response profiles, for the Jamieson, Howqua and Delatite Rivers, for three models identified on the same calibration period 6. All three catchments have equal drainage area (Table 2.1) and similar vegetation structure. The main difference
Figure 2.2. Observed (solid line), modelled (dashed line) streamflow (cumeecs) and error for calibration period 6 (1981-1982) for all 6 upstream catchments.
Figure 2.2. (continued) Observed (solid line), modelled (dashed line) streamflow (curecs) and error for calibration period 6 (1981-1982) for all 6 upstream catchments.
Table 2.3. Model efficiency values (see definition in Section 2.5.1) for calibration of the upstream catchments

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<th>405227</th>
<th>405218</th>
<th>405215</th>
<th>405214</th>
<th>405251</th>
<th>Composite catchment*</th>
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</tbody>
</table>

- denotes model's poor performance (E < 0.700)
* denotes composite catchment consisting of total daily flows for the Upper Goulburn, Big, Jamieson, Howqua and Delatite Rivers.

between them is the humidity level: the Jamieson River is located in a more humid area, Howqua is less humid and Delatite is the driest catchment of these three. This figure demonstrates that the total and slow flow hydrographs become steeper with decreasing humidity whereas the rate of drying of the catchment \( r_{w/k} \) accelerates with temperature for less humid catchments. The catchment wetness index \( s_k \) histograms quantify the sensitivity of effective rainfall, and hence runoff, to raw rainfall (see equation (2.1)). The histograms reflect higher probabilities for the larger values of \( s_k \) for wetter regions, whereas the percentage of small values of \( s_k \) is higher for dry catchments. These profiles illustrate how the DRC values reflect physical properties of the catchments.
Figure 2.3. Response profiles of three rivers upstream of Lake Eildon, using parameters estimated in calibration period 6. The Jamieson River (left) is the wettest catchment, the Howqua River (centre) has the mean level of humidity and the Delatite River (right) is the driest of the three.
In order to check the consistency of the results obtained, simulation runs were performed over the whole common period of observation (1975-1990) with each of the calibrated models. That is, the values of the parameters $\tau_w$, $f$, $c$, and the coefficients in the linear combination (2.2), optimised during the calibration runs, were used for modelling the streamflow using the rainfall and temperature series for the whole 20-year period. The efficiency coefficients $E$ and mean daily bias (absolute error) of modelled stream discharge for these simulation tests are shown in Table 2.4.

2.5.2. The composite catchment

Five catchments upstream of Lake Eildon (Big, Upper Goulburn, Jamieson, Delatite and Howqua Rivers) were considered as one composite catchment and their total daily flow calculated. With these data, and the Jamieson P.O. precipitation and Lake Eildon temperature records, models were identified on the same set of two year calibration periods chosen for each of the rivers separately (see Table 2.3). The model fit to the streamflow of the 5 rivers in the composite catchment ($E=0.945$ and the bias $B=0.29$ for CP 6) gave a similar result to the sum of the 5 individually modelled streamflows ($E=0.953$, $B=0.62$). The model fit results of these two identification strategies for CP 6 are shown in Figure 2.4.

The form of the model for the composite catchment is the same as for any of the individual catchments, for both the non-linear loss module (2.1) with 2 parameters and the linear module (2.2) with 4 parameters. The sum of the individual models, incorporating $6 \times 5 = 30$ parameters, is well approximated by the six parameter model, partly due to the fact that 10 exponential
Table 2.4. Simulation statistics with two-year calibrated models over period 1975-1990 for the upstream catchments: model efficiency $E$ and Bias (mean daily error in cumecs). Bold values denote the best selected models (see Section 2.6) for each catchment.

<table>
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Figure 2.4. Total streamflow model fit and error (below) for a composite catchment (left) and the sum of modelled streamflow for the five individual upstream catchments (right).
decays can be fitted by two. This exercise illustrates that the information content in precipitation-streamflow data in humid catchments is sufficient to warrant models of limited complexity only (see Jakeman and Hornberger, 1993). Another lesson from this exercise is that our model form can be used to model streamflow over a wide range of humid catchment sizes. The upper limit for this size will be determined principally by the adequacy of the precipitation data used to represent the areal cover of the catchment being modelled.

2.5.3. Downstream catchments

The common period of observation, 1970-1990 here, was divided into 10 non-overlapping two-year calibration periods. The model was calibrated over each of those periods (see Table 2.5 and Figure 2.5). The results of simulation runs over the entire 20 year period are presented in Table 2.6.

Table 2.5. $E$ values for calibration results for downstream catchments

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- denotes model's poor performance ($E < 0.700$)
Table 2.6. Simulation over whole period for the downstream catchments. E and Bias (mean daily error in cumecs). Bold values denote the best selected model for downstream catchments.

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<td>0.691</td>
<td>0.634</td>
<td>0.670</td>
<td>0.673</td>
</tr>
<tr>
<td></td>
<td>-0.95</td>
<td>1.87</td>
<td>0.05</td>
<td>0.02</td>
<td>-0.25</td>
</tr>
<tr>
<td>10</td>
<td>0.676</td>
<td>0.749</td>
<td>0.625</td>
<td></td>
<td>0.579</td>
</tr>
<tr>
<td></td>
<td>-0.49</td>
<td>1.39</td>
<td>0.13</td>
<td></td>
<td>-0.48</td>
</tr>
</tbody>
</table>

2.5.4. Sugarloaf Creek Catchment

Sugarloaf Creek is the only ephemeral stream among the selected catchments. A slightly different loss module was required to calibrate this river. Here the form proposed in Ye et al. (1995a) has been applied. It constitutes an extension of the first equation of the non-linear module (2.1) to the form:

\[ u_k = r_k \left[ \frac{s_k + s_{k-1}}{2} \right]^\gamma, \]
where $v$ is an additional parameter to be optimised. This parameter accentuates the non-linear dependence of effective rainfall on the catchment wetness status of the catchment. Figure 2.5 illustrates the model fit obtained for calibration period 7 on Sugarloaf Creek.

2.6. Selection of the best models (the Goulburn Basin)

For each of the 11 catchments (The Big, Upper Goulburn, Jamieson, Howqua and Delatite Rivers and Brankeet Creek upstream of Lake Eildon, and the Rubicon, Acheron, Murrindindi, Yea Rivers and King Parrot Creek downstream), each of the two-year calibrated models was investigated to ascertain which gave the best performance in predicting the impact of climate variability on streamflow over the period of streamflow observation. This requires selection of performance statistics for quantifying the quality of model fit either for calibration or simulation runs. Two principal statistics used are the model efficiency $E$ and bias $B$. We aimed to optimise both of these for each catchment because they reflect the dispersion of modelled values from observed and the ability to predict the absolute supply of water to stream on average. The best values for $E$ and $B$ were taken for the long term simulation run over the common observation period: 1975-1990 and 1970-1990 for catchments in the upstream and downstream groups, respectively. The selected models are indicated by bold in Tables 2.4 and 2.6. A test of the historical variability of the annual discharge for the selected model (see Section 2.7) was implemented for the rivers with a history of observation considerably longer than the common period of observation in order to estimate how well the model performs for the longer periods.

In order to test whether the best model for each catchment yields acceptable volumetric error in mean discharge for each of the 12 months of the year, a comparison of mean monthly
Figure 2.5. Observed (solid line), modelled (dashed line) streamflow and error (below) for calibration period 6 (1981-1982) and 7 (1983-1984, for Sugarloaf Creek) for 6 downstream catchments.
Figure 2.5. (continued) Observed (solid line), modelled (dashed line) streamflow and error (below) for calibration period 6 (1981-1982) and 7 (1983-1984, for Sugarloaf Creek) for 6 downstream catchments.
volumes of observed and simulated streamflow was also undertaken. This comparison was performed for simulation runs over the common observation period. Figure 2.6 shows the mean monthly observed discharge and the simulated discharge for the best selected models obtained for the Goulburn River at Doherty's and for the Jamieson River at Gerrans Bridge. These best models were calibrated on CP 10 and 11, respectively (see bold entries in Table 2.4). The results for these two catchments are indicative of the range of average monthly performance.

2.7. Historical variability (the Big and Jamieson Rivers)

Historical precipitation data are available at Jamieson P.O. since 1888 with a small gap from 1917 to 1922. This gap was filled using precipitation recorded at Woods Point (83033) and at Mansfield P.O. (83019). The associated historical temperature record was inferred using data from the Melbourne meteorological station and its linear regression with Lake Eildon temperature over the 20 year interval when the records from the latter station are available. The results of this approach for the Big and Jamieson Rivers are shown in Figure 2.7. The mean relative model errors calculated over the period when observed data were available (1960-1989) are 4% and 3% for the Big and Jamieson Rivers, respectively. Note the increase in rainfall for the period after 1945 compared with the period 1890-1945, described in Pittock (1975, 1981). The good quality of approximation obtained for measured values of annual discharge allows us to use the model with some confidence in order to estimate the effects of climate variability and possible climate impact in the selected area. This is necessary because the measured streamflow series are not long enough (often shorter than 20 years) to provide the data sufficient for statistical analysis of changes in river discharge.
Figure 2.6. Mean monthly observed (circles) and modelled (squares) discharge (1000 ML) shown for the Goulburn River at Dohertys and Jamieson River. Upper row - monthly discharge distributions, lower row - modelled values against observed values; 1:1 line is shown.
Figure 2.7a. Simulation on the basis of long term historical climatological data for the Big River. 5-year running mean values are calculated for precipitation (above), temperature (middle) and the best model (below). The mean values for two historical periods (1890-1945 and 1945-1990) are shown.
Figure 2.7b. Simulation on the basis of long term historical climatological data for the Jamieson River catchment. 5-year running mean values are calculated for precipitation (above), temperature (middle) and the best model (below). The mean values for two historical periods (1890-1945 and 1945-1990) are shown.
The associated simulations of the daily catchment wetness index $S_k$ are shown in Figure 2.8 for four of the upstream catchments. This coefficient can be used to characterise extreme events such as droughts. For instance, the drought of 1982 is clearly reflected by the local minimums of the $S_k$ -function in Figure 2.8 for all rivers under consideration. Such information is very useful for future analysis of possible climate impact on drought frequency in the Basin.

2.8. Model performance for the catchments of the Ovens Basin

Five catchments were selected in the Basin in order to consider all rivers contributing substantial water to the main stream of the Ovens River. These catchments are listed in Table 2.7 and are shown in Figure 2.1b (Victorian Surface Water Information, 1984). The total discharge of these catchments constitutes approximately 70% of the total discharge of the Ovens River.

**Table 2.7. Catchments of the Ovens Basin (Victorian Surface Water Information, 1984)**

<table>
<thead>
<tr>
<th>Station number</th>
<th>River and station location</th>
<th>Mean annual discharge (ML)</th>
<th>Area (km²)</th>
<th>Commencement of continuous streamflow records</th>
</tr>
</thead>
<tbody>
<tr>
<td>403205</td>
<td>Ovens River at Bright</td>
<td>230,000</td>
<td>495</td>
<td>1944</td>
</tr>
<tr>
<td>403233</td>
<td>Buckland River at Harris Lane</td>
<td>243,000</td>
<td>435</td>
<td>1972</td>
</tr>
<tr>
<td>403222</td>
<td>Buffalo River at Abbeyard</td>
<td>178,000</td>
<td>425</td>
<td>1965</td>
</tr>
<tr>
<td>403218</td>
<td>Dandongadale River at Matong North</td>
<td>74,800</td>
<td>181</td>
<td>1962</td>
</tr>
<tr>
<td>403227</td>
<td>King River at Cheshunt</td>
<td>261,000</td>
<td>453</td>
<td>1967</td>
</tr>
</tbody>
</table>
Soil moisture coefficients for four upstream catchments

5 year running mean values

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Sk</td>
<td>0.50</td>
<td>0.40</td>
<td>0.30</td>
<td>0.20</td>
<td>0.10</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Big R. (227)
Goulburn R. (219)
Jamieson R. (218)
Delatite R. (214)

Figure 2.8. Mean annual values for a 90-year period simulation of the catchment wetness index $s_k$ in 4 upstream catchments.
Model calibration was performed with daily precipitation-temperature-streamflow time series during the common period of observation, 1969-1985, when records for all stations were available. The Buckland River is the only exception where continuous streamflow data are not available until 1973. The period has been divided into 9 calibration periods (CP) each with a duration of about two years. The first eight of them do not overlap whereas the ninth CP has 1 year overlapping with the eighth because of the unavailability of temperature data after 1985. Successful calibrations were obtained for each of these catchments. Only for the cases of the Upper Ovens, Buffalo and Dandongadale Rivers with CP number 7 (25/04/1981-14/04/1983) was model convergence unsuccessful. The calibration results, in terms of model efficiency, are summarised in Table 2.8. The model fit to the observed flow for the Upper Ovens, King and Buffalo Rivers on the CP 3 is shown in Figure 2.9. The model efficiency statistic $E$ for all stations and CP’s is given in Table 2.8.

2.9. Selection of the best models and historic variability of streamflow

In order to check the consistency of the results obtained, simulation or verification runs with daily precipitation and temperature inputs were performed over the whole common period of observation (1969-1985) with each of the calibrated models. That is, the values of the parameters of the model, optimised during the two-year calibration runs, were used for modelling the streamflow using the rainfall and temperature series for the whole 16-year period. The efficiency coefficients $E$ and mean daily bias for these simulation tests are shown in Table 2.9.
Table 2.8. Model efficiency values $E$ for calibration of the catchments of the Ovens Basin

<table>
<thead>
<tr>
<th>Station number CP</th>
<th>403205</th>
<th>403233</th>
<th>403222</th>
<th>403218</th>
<th>403227</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 18/06/69-08/03/71</td>
<td>0.874</td>
<td>n/d</td>
<td>0.876</td>
<td>0.884</td>
<td>0.837</td>
</tr>
<tr>
<td>2 09/03/71-08/03/73</td>
<td>0.903</td>
<td>n/d</td>
<td>0.857</td>
<td>0.854</td>
<td>0.757</td>
</tr>
<tr>
<td>3 08/03/73-08/03/75</td>
<td>0.859</td>
<td>0.846</td>
<td>0.806</td>
<td>0.790</td>
<td>0.830</td>
</tr>
<tr>
<td>4 29/03/75-27/03/77</td>
<td>0.902</td>
<td>0.900</td>
<td>0.906</td>
<td>0.915</td>
<td>0.917</td>
</tr>
<tr>
<td>5 27/03/77-27/03/79</td>
<td>0.898</td>
<td>0.863</td>
<td>0.860</td>
<td>0.832</td>
<td>0.711</td>
</tr>
<tr>
<td>6 27/03/79-26/03/81</td>
<td>0.788</td>
<td>0.854</td>
<td>0.851</td>
<td>0.903</td>
<td>0.818</td>
</tr>
<tr>
<td>7 25/04/81-16/11/82</td>
<td>-</td>
<td>0.821</td>
<td>-</td>
<td>-</td>
<td>0.848</td>
</tr>
<tr>
<td>8 15/04/83-14/04/85</td>
<td>0.930</td>
<td>0.903</td>
<td>0.916</td>
<td>0.928</td>
<td>0.897</td>
</tr>
<tr>
<td>9 30/03/84-20/12/85</td>
<td>0.928</td>
<td>0.912</td>
<td>0.915</td>
<td>0.934</td>
<td>0.829</td>
</tr>
</tbody>
</table>

- denotes models poor performance ($E < 0.700$)
n/d - streamflow data incomplete for this period.

For each of the five catchments, each of the two-year calibrated models was investigated to ascertain which gave the best performance in predicting the impact of climate variability on streamflow over the period of streamflow observation. Selection of statistics to choose the best model should depend upon the purposes of the model. The selection is based on a comparison of the efficiency statistics for the simulation run and mean absolute errors of a model over the common observation period, 1969-1985, for all catchments of the Ovens Basin. In the case of the Ovens Basin the best models almost always gave the minimum bias with the maximum efficiency. The selected models are indicated (in bold) in Table 2.9.
Table 2.9. Simulation with two-year calibrated models over the period 1969-1985 for the Ovens Basin catchments. $E$ (model efficiency) and Bias (mean daily absolute error in cumecs). Bold values denote the best selected models for each catchment.

<table>
<thead>
<tr>
<th>Station number</th>
<th>CP</th>
<th>403205</th>
<th>403233</th>
<th>403222</th>
<th>403218</th>
<th>403227</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.692</td>
<td>0.726</td>
<td>0.687</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.776</td>
<td>0.789</td>
<td>0.757</td>
<td>0.641</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.790</td>
<td>0.784</td>
<td>0.761</td>
<td>0.681</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.710</td>
<td>0.712</td>
<td>0.768</td>
<td>0.708</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>0.753</td>
<td>0.764</td>
<td>0.770</td>
<td>0.688</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>0.693</td>
<td></td>
<td></td>
<td></td>
<td>0.663</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>0.770</td>
<td>0.797</td>
<td>0.721</td>
<td>0.663</td>
<td>0.766</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>0.772</td>
<td>0.800</td>
<td>0.737</td>
<td>0.679</td>
<td>0.760</td>
<td></td>
</tr>
</tbody>
</table>

Historical simulation on an annual basis for the Big and Jamieson Rivers of the Goulburn Basin was described in Section 2.7. In this section the results of long term historical simulation for the rivers of the Goulburn and Ovens Basins are described. In order to implement this historical simulation and to investigate future climate impacts, all of the rivers are grouped into three natural sets as described in the Introduction to this Chapter. That is the catchments upstream of Lake Eildon in the Goulburn Basin, the catchments downstream of Lake Eildon and the catchments of the Ovens Basin.
Figure 2.9. Observed (solid line), modelled (dashed line) streamflow (c.m.ees) and error for calibration period 3 (1973-1975) for 3 catchments of the Ovens Basin.
Figures 2.10, 2.11 and 2.12 show 5-year running mean values for precipitation, temperature and modelled and measured aggregated streamflow (the sum of streamflow of all rivers in each cluster). The commencement dates for the Ovens Basin (1949) and for the catchments downstream of the Lake Eildon in the Goulburn Basin (1958) were defined by the latest commencement date of precipitation records used for this area. The commencement date of 1945 was selected for the upper Goulburn. The associated historical temperature record was inferred using data from the Melbourne Regional Office meteorological station (N 86071) and its linear regression with Lake Eildon temperature over the interval when the records from the latter station are not available. A similar procedure was applied for the temperatures recorded at the Mt. Buffalo meteorological station which was used for calibration in the Ovens Basin. In order to check how sensitive the model is to the temperature records chosen as a basis for regression, historical simulation for the Ovens Basin was performed twice using Melbourne temperature and temperature taken from the Mildura airport meteorological station (N 76031) as a basis for linear regression. The difference between these two station is that Melbourne is located on the seashore whereas Mildura is a continental station. Therefore the temperature fluctuations at the first station are smoother than at the second. The results obtained show little difference between these two cases when the model was applied with the same values of the parameters.

For the period of streamflow availability, the mean relative errors, calculated as a ratio of the absolute value of the difference between modelled and measured annual flows to measured annual flow, are 5%, 8% and 5% respectively for the Upper and Lower parts of the Goulburn Basin and for the Ovens Basin.
Figure 2.11. Simulation of discharge on the basis of long term historical climate data for the Goulburn catchments downstream of Lake Eildon. 5-year running mean values are shown for precipitation (above), temperature (middle), discharge and the best model of streamflow (below).
Figure 2.12. Simulation of discharge on the basis of long term historical climate data for the catchments of the Ovens Basin. 5-year running mean values are shown for precipitation (above), temperature (middle), discharge and the best model of streamflow (below).
A test of the consistency of the results obtained was performed, by estimating how sensitive the mean relative errors are to the various models calibrated on different two year periods. Figure 2.13 indicates the level of consistency for modelling the integral flow of the Ovens Basin using the 6 best models for all 5 rivers of the Ovens Basin. The rank of the model indicated along the horizontal axis is from lowest to highest accuracy in terms of relative error. The first 4-5 models provide almost the same accuracy in approximation of measured streamflow over a period of 11 years of simulation. The variation between different models is explained by the fact that good convergence is provided for different values of the parameters of the non-linear module of the model (τw and f) on different CP's. Sometimes the range of these parameter values is rather high. For instance the values of τw and f parameters are scattered from (4, 2.2) on CP 5 to (16, 3.2) on CP 6 for the Upper Ovens River. However, it is assumed that the model with a higher value of efficiency and lower bias better reflects the physical properties of the catchment considered.

2.10. Conclusions

The IHACRES model has been applied for the first time on a large scale over two Basins. The total drainage area covered by the catchments of the Goulburn and Ovens Basin is about 6,500 km². The main result is that the IHACRES model can be used to model streamflow over a wide range of catchment sizes. The upper limit for the area under consideration will be determined principally by the adequacy of the precipitation data used to represent the areal cover of the catchment being modelled.
Figure 2.13. The mean relative errors for aggregated flow of the Ovens Basin obtained using the 6 best models for all 5 rivers of the Ovens Basin. The rank of the model along the horizontal axis is from lowest to highest.
Successful calibrations of the rainfall-runoff model were performed for 12 rivers contributing streamflow to the Goulburn Basin. The models were tested by simulation over the entire common period of observation for upstream and downstream catchments. The results of this test showed that the models obtained approximate the observed streamflow with reasonable volumetric error.

Successful calibrations of the IHACRES rainfall-runoff model have also been performed for 5 major rivers contributing streamflow to the Ovens Basin. The total discharge of the rivers modelled constitutes approximately 70% of the total discharge of these two Basins. The mean relative errors in annual discharge, calculated for a simulation run over the whole period of streamflow recording for the three groups of catchments (upper and lower parts of the Goulburn Basin and the Ovens Basin) are from 5% to 8%. This indicates the reliability of the model for estimation of possible climate impact on streamflow under current vegetation conditions in the region under study.

The effect of historical climate variability on streamflow and a catchment wetness index has been investigated. The models can be used as a basis for estimation of the potential impact of climatic change on water availability for irrigation and on the frequency distribution of extreme events such as droughts.
CHAPTER 3

ESTIMATION OF POSSIBLE CLIMATE CHANGE IMPACTS ON WATER AVAILABILITY, EXTREME FLOW EVENTS AND SOIL MOISTURE IN THE GOULBURN AND OVEN BASINS

Summary

The IHACRES models developed in Chapter 2 were used for estimation of the potential impact of climatic change on water availability for irrigation using a range of climate scenarios developed in the Division of Atmospheric Research, CSIRO. This allows conditional estimates to be made of water supply in these Basins for the periods 2030 and 2070 under current vegetation conditions. Projecting the future hydrologic regime in this region is extremely important, in particular for supporting irrigation management of the Basin.

Results were characterised in terms of the ‘most wet’ and ‘most dry’ scenarios for the years 2030 and 2070. The frequency of high flow was found to increase for the scenarios providing the maximum amount of water; to 50% at 2030 and 100% at 2070. The probability of high flow for the ‘dry’ scenarios rapidly decreases for these dates. Drought frequency, as defined by a soil wetness index, increased 35% for the ‘dry’ scenario at 2030 and 80% for this scenario at 2070.
3.1. Introduction

The industrially induced increasing concentration of greenhouse gases in the Earth’s atmosphere changes its radiative balance, and is expected to lead to increases in temperature, and changes in precipitation and other climatic patterns (e.g. Houghton et al., 1990). The simulation of future climate change due to increased concentration of greenhouse gases is usually performed with Global Climate Models, which simulate the global interaction between the atmosphere, ocean and land surface. An overview of existing climate models is outside the scope of this work, but adequate references can be found for instance in Tucker (1988), Pittock (1988, 1993), Houghton et al. (1990, 1992) and Whetton et al. (1994). Pittock (1988) emphasised the high level of uncertainty of existing climate models and suggested concentrating on the establishment of threshold levels for various effects and changes in the frequency of extreme events. This approach has been used to estimate changes in stream discharge under a range of climate scenarios.

As stressed earlier, the Goulburn Basin and the Ovens Basin of the Murray-Darling Drainage Division examined here are important contributors to irrigation supply in the state of Victoria. The impacts of climate on water availability in this region are of interest for planning purposes; the water resources of the Goulburn Basin provide approximately 40% of total irrigation water use in Victoria. Analysis of possible impacts was performed on the three groups of catchments defined in Chapter 2:

1. The catchments upstream of Lake Eildon in the Goulburn Basin (Figure 2.1a): the Big, Upper Goulburn, Jamieson and Delatite Rivers. (The Howqua River and Brankeet Creek were excluded from consideration because observed flow records are available for these catchments only from 1973 and 1971, respectively);
2. The catchments downstream of Lake Eildon (Figure 2.1a): the Rubicon, Acheron, Murrindindi and Yea Rivers and King Parrot Creek (although straightforward, Sugarloaf Creek was not considered in this analysis; a different structure of the model was applied for modelling its streamflow, see Section 2.5.4);

3. The catchments of the Ovens Basin (Figure 2.1b): the Upper Ovens, Buckland, Buffalo, Dandongadale and King Rivers.

These rivers provide approximately 70% of the total discharge for these two Basins. While there is some snowfall in the catchments of these Basins, they are treated as snow free in the modelling undertaken in this work. The area with elevation above 1400 m, where a large proportion of winter precipitation falls as snow, is relatively small for these Basins.

The lumped parameter rainfall-runoff model, IHACRES was successfully applied to the catchments in the Goulburn and Ovens Basins in Chapter 2. The reliability of the models calibrated on the Goulburn and Ovens catchments allows their use for estimation of possible climate change impact on the water supply of these Basins. Scenarios developed in the Division of Atmospheric Research CSIRO (Whetton, 1993) were used to produce the daily precipitation and temperature data relevant for climate at 2030 and 2070. These scenarios developed for the Southern coastal region of Australia (less than 200 km from the coast) provide a warming in the year 2030 in the range 0.5 - 2.0 degrees and in 2070 in the range 1.0 - 5.0 degrees. The rainfall change scenarios for the Victorian Alps are 0 - +20% for the summer half-year and -10% - +10% for the winter half-year in 2030. In 2070 this change is 0 - +40% and -20 - +20% respectively. In order to characterise a range of uncertainty for future climate changes, two scenarios were selected for climate at these two points in time: ‘most wet’ (minimum warming with maximum increase of rainfall) and ‘most dry’ (maximum warming with maximum decrease of rainfall).
The IHACRES model was used to calculate the daily, monthly and annual streamflow for these scenarios. Time series of climate data were generated by simply transforming historical series. Streamflow was estimated for 'most wet' and 'most dry' scenarios for 2030 and 2070 respectively. The climate impact was estimated for mean monthly and annual discharge in the rivers of the selected Basins.

3.2. Climate scenarios

The climate scenarios developed in the Climate Impact Group, CSIRO Division of Atmospheric Research have been described in CIG (1992) and Whetton (1993). The scenarios provide the changes for two main climatological variables, temperature and precipitation, for two periods in the future: 2030 and 2070. They are based on scenarios of future global warming produced by Wigley and Raper (1992) and regional results of five recent GCM equilibrium experiments (including two GCMs from CSIRO and the Australian Bureau of Meteorology) analysed by CSIRO which provided information on possible regional climatic changes. The five GCMs considered are: BMRC (Colman et al., 1994), CSIRO9, (McGregor et al., 1993), CCC (McFarlane et al., 1992), GFDLH and UKMOH (Houghton et al., 1990). The dynamics of future global warming are shown in Figure 3.1. This diagram indicates that the average global warming ranges from 0.6°C to 1.7°C by 2030 and from 1.0°C to 3.9°C by 2070. These large ranges take into account two major sources of uncertainty: the range of possible future greenhouse gas emissions (Houghton et al., 1992); and the range in the estimated global sensitivity of climate to the concentration of greenhouse gases in the atmosphere (1.5°C to 4.5°C equilibrium warming for a doubling of CO₂).
The information about regional patterns of climate response are based on the regional results of five recent GCM equilibrium experiments. The regional response patterns of temperature were provided for three broad regions of Australia: Northern Coast (north of about 25° S), Southern Coast (south of about 25° S) and Inland (more than about 200 km from the coast). These patterns, expressed as coefficients of local warming per degree global warming, are 0.3 - 1.0, 0.8 - 1.2 and 0.5 - 1.4, respectively.

The regional precipitation pattern for the summer period (November to April) is the same for the whole Australian continent, and is estimated as 0 - +10% rainfall change per degree global warming. In order to provide the winter (May to October) regional precipitation pattern, the Australian continent is divided into three sub-regions (denoted as A, B and C). No winter scenarios were given for that part of Australia with very low winter rainfall. The winter responses per degree of global warming are 0 - -5%, -5% - +5% and 0 - +5% for the sub-regions known as A, B

Figure 3.1. Scenarios for future global warming from Wigley and Raper (1992).
and C respectively. The Goulburn and Ovens Basins belong to the Southern Coast for temperature regionalisation and to sub-region B for rainfall regionalisation.

Two extreme cases for climate change were considered for the period 2030 and 2070. The first is the case providing the minimum amount of water runoff (the ‘most dry’ scenario) and the second, the maximum value of runoff (the ‘most wet’ scenario). The ‘most dry’ case is reached for the case of maximum increase in temperature and the maximum reduction in precipitation. The ‘most wet’ case is reached with the maximum increase in precipitation and the least warming that can be related to this level of increased rainfall (the changes in

Figure 3.2. The sub-regions used for winter rainfall change from CIG (1992).
temperature and precipitation had to be considered with regard to the trend of global warming). The fact that this case yields the highest runoff is not obvious. The level of evaporation increases very sharply with increasing temperature. The scenarios for 2030 and 2070 with minimum warming (0.5° and 1.0° respectively) but with the correspondingly lower increases in rainfall were also considered and were found to provide less runoff than the scenarios with the maximum increase in precipitation. This way of using the CSIRO scenarios is similar to that used by Chiew et al. (1995).

The climate scenarios used for the region under consideration are summarised in Table 3.1. The scenarios were applied by changing all observed daily temperatures by the scenario increment and by changing the rainfall by the scenario percentage on all days with rain.

Table 3.1. Climate scenarios for the Victorian Alps.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Warming (°C)</th>
<th>Changes in precipitation (summer)</th>
<th>Changes in precipitation (winter)</th>
</tr>
</thead>
<tbody>
<tr>
<td>‘most dry’ 2030</td>
<td>2</td>
<td>0%</td>
<td>-10%</td>
</tr>
<tr>
<td>‘most wet’ 2030</td>
<td>1.5</td>
<td>+20%</td>
<td>+10%</td>
</tr>
<tr>
<td>‘most dry’ 2070</td>
<td>5</td>
<td>0%</td>
<td>-20%</td>
</tr>
<tr>
<td>‘most wet’ 2070</td>
<td>3</td>
<td>+40%</td>
<td>+20%</td>
</tr>
</tbody>
</table>

3.3. Climate impact on streamflow

3.3.1. Background

Several publications have been devoted to the problem of estimating possible climate impacts on streamflow. Leavesley (1994) provided a review of this problem and there a list of relevant references can be found. Klemes (1985) suggested general principles of validation and testing of hydrological models applied for simulation of streamflow under future climate conditions.
Wigley and Jones (1985) applied a water-balance model for such studies. The problem of the
streamflow response to climate variation is stated in Nemec and Schaake (1982). Results of
deterministic modelling using the Sacramento Soil Moisture Accounting Model was applied
to quantify the influence of climate variations on the streamflow of several arid and humid
catchments and on reservoir storage systems. The main disadvantage of these studies is that
they were concerned more with scaling of the rainfall-runoff models for different ranges of
input climatic data rather than with physically motivated climate scenarios for the regions
under study.

Two studies in Australia have avoided this problem. Nathan et al. (1988) applied the
deterministic, conceptual rainfall-runoff model, HYDROLOG, to study climate impact on
runoff in two Australian catchments. One of them (Myponga Weir in Southern Australia) has
winter dominated rainfall whereas summer rainfall is dominant in the second (Moogerah Dam
in Queensland). The climate scenarios used in this work are slightly different from scenarios
recently provided in CIG (1992) and Whetton (1993). The 50% increase in summer, autumn
and spring rainfall, coupled with a 10% reduction in evaporation for Moogerah catchments,
results in a 280% increase in annual flow. The 20% decrease of winter rainfall with 10%
increase of evaporation gave a 25% decrease in annual flow.

Chiew et al. (1995) followed the above approach using the Modified HYDROLOG model in
order to model 28 benchmark catchments in Australia and estimate the climate impact on
their streamflow. The climate scenarios used in this work were taken from CIG (1992), but
were slightly modified and are not precisely the same as in our work. Only one catchment is
the same as in our analysis (the Dandongadale River, stream gauging station N 403218) and
another two of the 28 catchments are located close to the Ovens and Goulburn Basins
(stations N 401554 and N 401212 from the Upper Murray Basin). The scenarios for 2030
provided changes in annual flow for the Dandongadale River in the range -5% - +5%. Chiew et al. (1995) concluded that, for south-east regions of Australia, runoff varies in the range 20% - +20% under climate scenarios for 2030.

Close (1988) modelled about 10 rivers of the Murray-Darling Drainage Division (including the Goulburn and Ovens Rivers) and estimated the possible climate impact on its water resources using the Murray-Darling Basin Commission empirical model. He concluded that the effect of higher concentrations of CO$_2$ in the atmosphere will be to increase tributary flows over almost all the Division in the next 30 years. However, his analysis assumes that climatic changes over the period 1913 to 1978 are analogous to the changes that can be expected from a 50% increase in atmospheric CO$_2$ concentrations which could occur in the next 30 years.

### 3.3.2. Scaling of the model

The problem of whether the parameters of the IHACRES model depend on climatic conditions in the calibration period was discussed in Jakeman et al. (1993, 1996). It was established that, although the model parameters vary, the variation is not substantial and does not affect predictions in a major way. Models calibrated on wet periods and simulated on dry periods performed almost as well as models calibrated on dry periods. The converse was equally valid. But it should be emphasised that calibrations in the case of the rivers of the Goulburn and Ovens Basin were performed for relatively uniform vegetation conditions in the area considered. Considerable changes in land use or deforestation in this area in the future may provide more dramatic changes to discharge in these Basins.
3.3.3. Climate impact on the annual and monthly streamflow

Figure 3.3 shows the response of the integral flow of the Ovens Basin for the separate temperature and precipitation changes to the 1973-1985 records. The changes in mean annual streamflow after application of the scenarios listed in Table 3.1 are summarised in Table 3.2.

Table 3.2. Climate impact on annual precipitation and streamflow for selected scenarios.

<table>
<thead>
<tr>
<th>The Goulburn Basin (upper part)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period</td>
</tr>
<tr>
<td>'most dry' scenario</td>
</tr>
<tr>
<td>'most wet' scenario</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>The Goulburn Basin (lower part)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period</td>
</tr>
<tr>
<td>'most dry' scenario</td>
</tr>
<tr>
<td>'most wet' scenario</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>The Ovens Basin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period</td>
</tr>
<tr>
<td>'most dry' scenario</td>
</tr>
<tr>
<td>'most wet' scenario</td>
</tr>
</tbody>
</table>

The small difference in the annual rainfall changes for different clusters of catchments is related to the fact that the part of precipitation occurring in the winter period is not exactly the same for all groups of catchments. Figure 3.4 shows how the annual discharge is affected by different climate scenarios for all groups of catchments selected and all scenarios from...
Figure 3.3. Streamflow response to the changes in (a) temperature and (b) precipitation for the Ovens Basin.
Table 3.2; Figure 3.4a shows results for the catchments upstream of Lake Eildon in the Goulburn Basin, Figure 3.4b for the catchments downstream of Lake Eildon in the Goulburn Basin and Figure 3.4c for the catchments of the Ovens Basin. Streamflow scenarios for 2030 (dotted lines) and for 2070 (dot-dashed lines) might be provisionally interpreted as maximum ('most wet' scenarios) and minimum ('most dry' scenarios) extrema defining the volumetric domain wherein the annual streamflow can vary in response to climate at these points in time.

Figure 3.5 exemplifies of how these scenarios affect the mean monthly flows. The case of the Ovens Basin is considered and the historical dynamics of monthly discharge for February (summer) and August (winter) are presented. The dashed line represents the measured values of mean monthly discharge for these months and reflects the quality of the model for simulation of monthly discharge (mean relative errors are 6% and 8% for February and August, respectively). The slight overestimation of modelled discharge for August can be explained by the snow accumulation processes in the Upper Ovens catchments which were not taken into consideration. Figure 3.5 also shows that in summer the relative increase of flow can be higher than in winter. The climate impact on mean monthly flow in the lower part of the Goulburn Basin for each month of the year is summarised in Figure 3.6.

The 'most wet' scenarios in each case lead to negligible change (except in the late summer-early autumn period) as the effect of a small warming cancels the effect of increasing rainfall. For 'most dry' scenarios in each case a very substantial reduction in streamflow is found; about 35% in 2030 and 60% in 2070.
Figure 3.4a. Climate impact on annual streamflow for the 4 scenarios listed in Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered provisionally as upper and lower thresholds for possible annual streamflow fluctuations for future climate change.

(The catchments of the Goulburn Basin upstream of Lake Eildon).
Figure 3.4b. Climate impact on annual streamflow for the 4 scenarios listed in Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered provisionally as upper and lower thresholds for possible annual streamflow fluctuations for future climate change. (The catchments of the Goulburn Basin downstream of Lake Eildon.)
Figure 3.4c. Climate impact on annual streamflow for the 4 scenarios listed in Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered provisionally as upper and lower thresholds for possible annual streamflow fluctuations for future climate change. (The catchments of the Ovens Basin).
Figure 3.5. Climate impact on monthly streamflow in the Ovens Basin for 2070 scenarios from Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered provisionally as upper and lower thresholds for possible February and August streamflow fluctuations for future climate change. Dashed line - measured streamflow.
The catchments downstream of Lake Eildon

Figure 3.6. Climate impact on mean monthly discharge for the catchments of the Goulburn Basin downstream of Lake Eildon.
3.3.4. Extreme events

Gordon et al. (1992) and Whetton et al. (1993) analysed daily rainfall output for Australia from the CSIRO GCM with four (CSIRO4) and nine (CSIRO9) vertical levels respectively. They noted that daily rainfall intensity was simulated to increase in general and the return period of heavy rainfall events decreased. The number of rainy days either decreased or changed little.

Here the changes in the frequency of high flow resulting from the application of the climate change scenarios are examined. In particularly, the changes for the ‘most wet’ scenarios for 2030 and 2070 are accentuated. Because the number of rainy days are not changed, the ‘most wet’ scenario implies increases in daily rainfall intensity. This is in line with what was seen in the simulations of Gordon et al. (1992) and Whetton et al. (1993). However, they see a tendency for the number of rainy days to decline even when rainfall increases, so the increases in rainfall intensity applied here may well be conservative. Under the ‘most dry’ scenario, rainfall reductions are achieved by reduced rainfall intensity and no change in the number of rainy days. The results of Gordon et al. (1992) and Whetton et al. (1993) would suggest this overestimates reduction in rainfall intensity.

Application of the IHACRES model allows definition of the term ‘flood’ directly in the terms of critical values of streamflow. Figure 3.7 demonstrates how the frequency of August, September and October discharge (months with the maximum mean value of streamflow discharge for the majority of the rivers under study) varies with time (for present, 2030 and 2070) for the Upper Ovens River at Bright (gauging station 403205). These results show that the ‘dry’ scenarios provide a decrease in frequency of high flow whereas the ‘wet’ scenarios provide...
Figure 3.7a. Histograms of daily streamflow (for a period of August, September and October) for the present and the 2030 and 2070 'most dry' scenarios for the Upper Ovens River at Bright (403205).
Figure 3.7b. Histograms of daily streamflow (for a period of August, September and October) for the present and the 2030 and 2070 'most wet' scenarios for the Upper Ovens River at Bright (403205).
an increase. If the threshold for discharge of 50 cumecs is chosen as anomalously high then the probability of high flow increases about 50% and 100% in 2030 and 2070, respectively (the probabilities of streamflow events with discharge greater than 50 cumecs are 0.022 at present, 0.031 at 2030 and 0.040 at 2070 for the ‘most wet’ scenarios, Figure 3.7b). It is notable that the wet scenarios provide little increase in average annual flow, but large increase in high flow frequency. The probability of high flow in the ‘most dry’ scenarios sharply reduces from 0.022 at present to 0.004 at 2030 and to a zero value at 2070 (Fig 3.7a).

Flood effects are specially important in the lower, highly populated and industrially developed parts of the Basins. Therefore routing of the rainfall-runoff further downstream would be valuable for producing forecasts of floods and droughts in the region for different climate scenarios.

In future the IHACRES model could be applied for estimating climatic impacts on drought frequency for different climate scenarios. Here it is specially significant to consider the ‘most dry’ scenarios for 2030 and 2070 where droughts might occur more frequently. The catchment wetness index of the model $S_k$ (see formula (2.1) in Section 2.4), could be used for calculating changes in the frequency of droughts. Some preliminary results produced for the single catchment (Upper Ovens at Bright, station N 403205) are shown in Figure 3.8. The histograms for the frequency of the soil wetness index $S_k$ were produced using the same historical records as previously (upper histogram), the ‘most dry’ scenario for 2030 (middle) and the ‘most dry’ scenario for 2070 (lower). The probability of $S_k$-events with magnitude less then 0.05 (this threshold is arbitrarily chosen as a definition of ‘drought’ here) increases by about 35% (from 0.17 to 0.23) for the present and the 2030 scenario and increases by about
Figure 3.8a. Histograms for soil wetness index for present and the 2030 and 2070 'most dry' scenarios. The case of the Upper Ovens River at Bright (403205) is considered.
Figure 3.8b. Histograms for soil wetness index for present and the 2030 and 2070 ‘most wet’ scenarios. The case of the Upper Ovens River at Bright (403205) is considered.
80% (from 0.17 to 0.31) for the ‘most dry’ scenario for 2070 (Figure 3.8a). These probabilities remain much the same for the ‘most wet’ scenarios (Figure 3.8b); their values are 0.17, 0.17 and 0.19 at present, at 2030 and at 2070 respectively.

3.4. Discussion

While climate scenarios will doubtless be updated from time to time and methods of generating daily climate time series for the future will become more sophisticated, a very basic question is the applicability of the model for predicting streamflow under different climate assumptions. It is not entirely possible to check how satisfactorily the model works for the hypothetically high temperatures which are assumed to occur in the future under global warming but which have never occurred during the instrumented period. However, a useful test showing how well the model performs for a range of different temperature clusters was implemented. Figure 3.9 shows the distribution, according to its average temperature class, of mean daily flow for the observed data and the model simulation over a 45 year period (1945 to 1990) for the Upper Ovens River at Bright. Mean daily flow was calculated separately for each temperature interval with a class width of one degree. The figure shows a good fit for model to observed data for every temperature category in a range of 2° - 30°. The mean relative error calculated for this distribution is 0.043. The results of this test support the adequacy of applying of the model selected for the analysis of streamflow changes under different precipitation and temperature scenarios.

Another problem of the method applied is that only changes in the mean values of climatic patterns, such as temperature and precipitation, are considered in the scenarios considered. Possible changes in their variances and covariances might seriously affect the results especially the climate impact on extreme events. Clearly, the methodology of this work could
Figure 3.9. The distribution, according to its average temperature class, of mean daily flow for the observed data and the model simulation over the 45 year period (1945 to 1990) for the Upper Ovens River at Bright (403205). Mean daily flow was calculated separately for each temperature interval with a class width of one degree.
be followed by extending the use of climatic inputs with changing distribution. Without any hypothesis for this change, this has been omitted here. The analysis presented here also neglects the effect of vegetation changes in the catchments considered. Changes in atmospheric carbon dioxide levels may affect plant transpiration rates (e.g., 'reference') and Jakeman and Hornberger (1993) consider assumptions. Human changes to land cover in the future may also affect runoff and evapotranspiration rates.

The specific approach of this work is particularly apt when the interest is in specific catchments with gauged discharge recordings available and in current vegetation. If a general approach is required the effects of vegetation changes to handle ungauged catchments and to incorporate then the techniques of regionalisation should be considered (Jakeman et al., 1994c) where parameters of the precipitation-runoff model are inferred from landscape attributes. For example, Jakeman et al. (1994c) analysed how changes in catchment vegetation can affect the hydrologic response. The hydrologic regime in the Piccaninny catchment in Victoria was analysed before and after deforestation. They observed that the temperature modulation factor $f$ and the storage parameter $c$ decreased sharply when catchments in the region were deforested. Post and Jakeman (1996) have subsequently derived a relationship between the changes in the $c$ parameter and deforestation. Jakeman et al. (1994c) also showed how the various parameters of the IHACRES model are related to other landscape attributes in the region. For example, the recession rate of slow flow was related to catchment slope. Without using discharge measurements, Post and Jakeman (1996) subsequently obtained good results in predicting daily streamflow using precipitation, temperature and the IHACRES parameter values inferred from the landscape attribute relationships. This style of regional inference shows much promise and the reason for the new-found success is believed to be the relatively low level of parameterisation in IHACRES,
its reasonable structure (such that model parameters are not strongly variant with calibration period climate) and its high efficiency in predicting streamflow.

Two approaches aimed at reducing the level of uncertainty in regional climate change estimation based on global circulation climate modelling (GCM) should be mentioned. The first is the development of limited area models where ‘atmosphere-ocean-land surface’ interactions are considered within a limited region and external effects are represented by boundary conditions derived from GCM’s. The limited area model developed in the CSIRO Division of Atmospheric Research (DARLAM) has been applied at a spatial resolution of 125 km x 125 km and 60 km x 60 km for several regions of Australia (McGregor and Walsh, 1993, 1995). This finer resolution improves simulation of climate changes individually for each river in order to assess the changes in its discharge. The second approach is the method of generating stochastic climate time series (stochastic weather generators). This approach, developed for the Australian region, is described in Bates et al. (1993), Bates et al. (1994) and Charles et al. (1993) and makes use of detailed observed data. In doing so, it ensures that the multivariate distributional structure among climate variables is considered so that, for example, historic covariation can be maintained or perturbed, but not so far as to yield simulations of physically implausible climates.

3.5. Conclusions

Climate scenarios developed for the Australian region were applied for estimating the possible climate impact on water availability in these Basins. Two extreme cases were considered: a pessimistic scenario yielding a minimum amount of river runoff and an optimistic scenario yielding a maximum amount. These two cases might be considered the lower and upper limits respectively for total discharge of the rivers in the Goulburn and Ovens Basins under the
enhanced greenhouse effect. For two dates in the future, 2030 and 2070, the pessimistic forecast produced a 34 - 38% and 62 - 64% reduction in streamflow discharge respectively. The optimistic forecast produced changes of -3% - +4% and 0% - +6% in streamflow level for the same periods. As these latter values are very close to the predictive error in the model, the current streamflow discharge regime could be considered similar to the conditions provided by the latter scenario. In this case evaporation resulting from increased warming cancels the maximum possible increase in rainfall.

Frequency of high flow was found to increase for the 'wet' scenarios; to 50% at 2030 and 100% at 2070. The probability of high flow for the 'dry' scenarios rapidly decreases from 0.022 at present to 0.004 at 2030 and to a zero value at 2070. Drought frequency, as defined by a soil wetness index, increased 35% for the 'most dry' scenario at 2030 and 80% for the 'most dry' scenario at 2070. These results are consistent with the results obtained by Whetton et al. (1993) for but are more pessimistic regarding droughts.

Limitations of the approach are related to the high level of uncertainty in the estimated climatic patterns, mirrored in the large differences in streamflow values associated with the selected scenarios. Application of climatic time series derived from outputs of higher spatial resolution GCM's or "nested" Limited Area Models (LAMs) when they become available, in conjunction with the use of weather simulation models to guarantee an historic or selected multivariate distribution among climate variables, is suggested as a way in the near future to gain more precise predictions of streamflow.
CHAPTER 4

RUNOFF MODELLING FOR SNOW-AFFECTED CATCHMENTS IN THE AUSTRALIAN ALPINE REGION

Summary

Precipitation-runoff modelling was developed and applied to two large catchments of the Murray-Darling Basin, Australia: the Kiewa (552 km$^2$) and Mitta-Mitta (1,533 km$^2$) Rivers. As these catchments are located in the highest parts of the Australian alpine region in Eastern Victoria, snow melt/accumulation processes feature prominently in the hydrological regime of these rivers. Accordingly, a model was developed to compute equivalent rainfall from raw precipitation records, taking into consideration snow melt/accumulation processes in the different parts of these catchments. This model uses daily meteorological data as an input, determined on a daily basis over the whole region under consideration (2,085 km$^2$) using a spatial interpolation procedure with a resolution of 2.5 km x 2.5 km. The snow melt/accumulation model is based on a modified degree-day method and provides the equivalent amount of melted/accumulated water for each gridcell of the catchments considered. The method developed allows modelling of the melt/accumulation processes directly without requiring information about observed snow cover distribution in the area. Measured daily precipitation was converted to equivalent rainfall using minimum and maximum daily temperature and modelled equivalent (in mm of water),
accumulated in each particular gridcell for each day. The modelled snow depth and duration of the snow season were compared with point measurements of snow depth at several stations. Daily streamflow for the Kiewa and Mitta-Mitta Rivers was modelled with the rainfall-runoff model, IHACRES, using as an input the equivalent rainfall estimated by the snow melt/accumulation module and the mean daily temperature in each gridcell integrated over the whole catchments. Model calibration on two year periods was performed and subsequent simulation of streamflow over an 18-year period of observation with these calibrated models yields encouraging results for those wishing to use such a simplified approach. Given hypothesised daily precipitation and temperature, the model may be used to estimate future climate impacts under the assumption that the vegetation conditions in the area considered remain similar.

4.1. Introduction

4.1.1. Snow runoff models

Snow runoff models may be methodologically subdivided into two major groups: models based on empirical relationships between the hydro-meteorological characteristics of a catchment and models oriented to physical explanation of the processes of snow melt/formation. Over the past decade or more, spatially distributed snowpack models have been developed because of technological advances in remotely sensed data acquisition such as by air and space photography (Martinec 1973, Andersen 1982, Xianzhang et al. 1991), multispectral satellite observation (Martinec, 1991), gamma-ray survey (Dmitriev et al. 1973, Goodison et al. 1986) and microwave probing (Wankiewicz 1991). The rapid improvements in relevant computer software associated with Geographical Information Systems has also contributed to this development. The spatially distributed approach allows the snowmelt/formation processes to be described separately for gridboxes with a resolution in
which the topography and physiography are assumed homogeneous. This is especially important for alpine regions where the altitude gradient is high.

The physical versus empirical classification is, on the one hand, very crude because there are no purely empirical or physical models and particular models usually use both approaches simultaneously. On the other hand, the classification is useful to help define the basic conception of the selected approach. It is important to separate publications concerned with modelling of the melt/accumulation process in the snow pack and those devoted to modelling of snow runoff. In the former case, the emphasis is on physical processes in snow, ice and water near the zero degree temperature point, while in the latter, it is on the practical purposes of accurate streamflow description.

4.1.2. Empirical models

Empirical models are usually based on air temperature data in order to calculate the amount of melted or accumulated water in the snowpack. Such an approach is called a degree-day (or temperature index) method. The degree-day method is defined and described in detail in U.S. Army, Corps of Engineers (1956, 1960). The core of this method is an assumption that the melt rate is linearly related to the difference between air temperature $T_a$ and a base threshold temperature $T_b$, below which there is no melting:

$$M = M_f (T_a - T_b),$$ (4.1)

where $M$ is snowmelt in mm and $M_f$ is a degree-day or melt factor.

A practical model of the snowmelt process based on the degree-day factor is described in Riley et al. (1973). They present three methods for estimating the snowmelt rate coefficient depending upon the time and space resolution of the model. The degree-day coefficient takes into account the values of radiation indices, albedo, vegetation transmission coefficient and precipitation rate. The advantage of this model is that it uses only data which are usually
measured in an instrumented catchment. Application of this approach in the experimental catchment of the Central Sierra Snow Laboratory, where the parameters defining the degree-day coefficient were obtained empirically, gave a good fit of modelled to observed snowpack.

An overview of empirical models which were used for short-term and long-term (seasonal) snow runoff forecasting was made by Quick (1973). Long-term forecasting is concerned with the seasonal volume or seasonal maximum of flow, when the time step is bigger than the response time, and channel routing in the Basin can be ignored. The most common type of such a forecasting technique is *multiple regression analysis* of past data concerning the amount of snow in a Basin and antecedent climatic conditions. The runoff coefficient method was also used for seasonal forecasting. The necessity to estimate these coefficients separately for snowmelt, rainfall and rainfall during snowmelt, and for open and forested areas, illustrates the complexity of this method. Short-term forecasting is a more difficult problem because it must take into account infiltration losses to soil moisture and groundwater and channel routing delay.

Ikebuchi et al. (1986) applied an empirical snow runoff model to the Ohura River Basin with a 1-hour time step. The model results show good prediction of snow depth both for years with little and heavy snowpack.

Moore (1993) applied the degree-day approach for modelling snowmelt processes using the relationship (4.1), as well as characterising the refreezing of liquid water held in the snow pack by:

$$F = C_f(T_b - T_d),$$

where $F$ is the amount of refreezing water in mm and $C_f$ is a refreezing coefficient. An innovation in this study was a module for routing water through the glacial drainage system, and the use of observed equilibrium line altitudes for nearby glaciers in order to remove the
uncertainty from the calibration of model parameters governing the accumulation and ablation processes. He applied a conceptual streamflow model with a snow melt/accumulation routine to the Lillooet River Basin (2,160 km$^2$) in Canada. He reviews eight studies applying conceptual streamflow models to glacierised catchments worldwide, with drainage areas ranging from 11.4 to 13,000 km$^2$.

4.1.3 Physical models

Anderson (1973) identifies the dominant variables of snow hydrology and the factors affecting the distribution of water equivalent in a snow covered area. While some of these factors, such as storm characteristics, areas with significant forest cover and wind direction, cannot be easily quantified, they are nevertheless considerably important for snow melt/formation modelling.

Some theoretical aspects concerning the long-range forecasting of seasonal snowmelt were reported in Popov (1973) and an equation for total snowmelt runoff was introduced. Its water equivalent was calculated as the difference of two integrals where the first represents the snowmelt in an active area, i.e. that part of the Basin from where snowmelt runoff is possible, and the second integral represents the amount of water retained in the active area, which is equal to total retention capacity. Usually, this value of soil retention capacity is obtained empirically for a given Basin using historical data. For practical use of this equation in the prediction of snowmelt runoff it is necessary to know an areal distribution of snow cover and surface soil capacity. The main difficulty of the method suggested is a lack of information about infiltration (the basic assumption was made that frozen soil with a temperature 2-3º below zero becomes impermeable for meltwater) and high irregularities in snow cover distribution. It was emphasised that the key problem of snow runoff prediction is estimation of meltwater absorption.
The modern theory of snowmelt/formation began with the introduction of an energy and mass balance approach (Anderson 1968, 1976). The sum of all energy inputs to the snow surface and all energy losses were calculated, and the residual energy was assumed to be used for melting snow. Morris (1991) provides a review of advanced physically based techniques for modelling of snowmelt/accumulation processes. She states that the next important step in snow modelling was made by Colbeck (1977) who applied equations describing flow transport in soil to water transport in wet snow because it also can be considered as a porous medium. Sulakvelidze (1959) first applied equations for heat transport in porous media in order to describe the temperature variations in snowpack. According to Morris (1991), the limitation of physically based models of snow is that they have been developed for 'unpolluted' snow that is a mixture of ice, water, water vapour and air. However, the basis for physically based snowmelt/formation models is so called 'mixture theory', the concept that snow can be regarded as a mixture of two components: air and water in its three phases. The mathematical theory for this method was developed in Kelly et al. (1986).

Another physically based model of snow formation and melt was described in Motovilov (1986). The snow is considered as a porous medium consisting of solid ice particles, and where melted water moves. Two basic assumptions were made: (1) there is no water in snow if the temperature is below zero, and (2) the liquid transport in the medium is explained by gravitational force only. Then a system of differential equations describing heat and moisture transfer is regarded as adequate for the process of snow formation/melt. A range of parameters was estimated through empirical formulae. The model was calibrated and tested in a high alpine area of western Tien-Shan at an experimental site known as the "Abramov glacier" at an elevation of 3,850 m. The model output related only to snow characteristics (depth, density and water equivalent) and no modelled runoff was computed.
Direct measurements have been undertaken in order to establish comparisons between empirical results and physically oriented models. A field experiment, undertaken in order to measure the energy exchange across the surface of a snow-covered, frozen lake in Norway, was described in Harding (1986). Radiation and evaporation were measured directly and the heat fluxes were estimated from profile measurements of wind and temperature. The water equivalent of snowpack was monitored during this experiment. The results obtained for the full energy balance model were compared with an empirical degree-day approach. The former agreed better with measurements of long-term mean snowmelt than the latter method.

The difficulty in applying physical models is the spatial estimation problem related to "extreme spatial heterogeneity of hydrologic environment" (Kimbauer et al., 1994). Another problem in applying such models is that they not only need many (some times more than 10) parameters to be estimated but very detailed meteorological and physical measurements are also required: precipitation and air temperature, snow temperature at different levels, snow density, cloudiness, wind direction etc. Such detailed observations are not available for a wide range of regions for a relatively long period. Sosedko and Kochelaba (1986) proposed the model 'Sneg-2' (Snow-2) of snowmelt runoff which uses only standard hydrometeorological data. It was applied for snowmelt runoff modelling in the Carpathians Mountains, western Ukraine. The model is very complex with several components describing the processes of snowmelt and water yield from snow, the overall distribution of snowmelt and rainfall water in the Basin, regulation effects in the region and river network routing. This model has a number of empirical relationships and 15 parameters.

Bloeschl et al. (1990) described the results of snowmelt modelling, based on an energy balance approach using physically based preset parameters, in the large (1,187 km²) Isel catchment in the Austrian Alps. The state of snow cover with elevation was characterised by distinguishing three zones (dry, partly soaked and soaked snowpack) with different melt and
drainage conditions. The performance of this model was assessed by comparing modelled and observed runoff and by analysing the simulated variations of Basin snow cover conditions reflected in boundaries between different snow zones.

4.1.4. Distributed models

Bloeschl et al. (1994) suggested defining a model as ‘distributed’ if it deals with spatially distributed hydrological data rather than with the input and output integrated over the whole Basin under consideration. A small experimental Laengental catchment (9.4 km²) in Tirol, Austria, was used by Bloeschl et al. (1991, 1994) in order to model snowmelt processes. The model used digital terrain data with a 25 m x 25 m spatial resolution. Energy balance models were applied to each gridcell taking into account the topographic properties of every individual site for accurate estimation of solar radiation patterns. Albedo was modelled using a simple ageing-curve approach introduced in Bloeschl (1991), i.e. albedo was assumed to decrease solely with the age of the snow surface. Meteorological data were extrapolated for every gridcell using the basic assumption that air temperature decreases and precipitation increases linearly with elevation. Model performance was verified using information on snow cover distribution in the catchment, estimated by weekly air photographs. The results showed the importance of the use of distributed data for snowmelt modelling.

Hatta et al. (1993) developed a spatially distributed snow runoff model with a resolution of 20 m x 20 m. The model was applied to the small (1.0 km²) Kannonsawa River Basin near Sapporo, Japan, in order to forecast snowmelt runoff on a 1-hour timestep. The model combined physical and empirical approaches and provided acceptable results for the practical purposes of snow runoff forecasting.

A spatially distributed physical model for snowmelt runoff was applied by Kuchment et al. (1986) to the Sosna River Basin (area 16,300 km²) in Russia. The Basin was subdivided into
200 finite elements according to their similarity in topography, soil type and land use. The snow-cover accumulation and snowmelt processes were described for each finite element by a system of two finite difference equations describing heat and moisture transfer, where a range of parameters were involved (temperature, soil porosity, hydraulic and thermal conductivities, heat capacity etc.). The processes were then integrated over the whole Basin using an infiltration model and routing model, taking into account the network of tributaries in the area. Mathematically this process was approximated by a two-dimensional kinematic wave equation. A range of parameters used were estimated empirically for their region, some of which were approximations in a 2-parameters γ-distribution. The method allowed spring maximum discharge to be predicted for the Basin selected.

The spatially distributed snow accumulation and ablation model developed by the National Weather Service, USA, calculates integrated snow water equivalent in snow-affected catchments to drive hydrological models for stream discharge prediction and flood forecasting. Carroll et al. (1995) developed the system, incorporating airborne as well as ground-based data, to estimate integrated snow water equivalent more precisely.

Kirnbauer et al. (1994) provide an overview of recent results of applying distributed models in hydrology, and a complete list of the relevant references can be found there. One of the most advantageous properties of distributed models mentioned in that paper is that, unlike point-based models, they can cope with the problem of representing the spatial variability of snow processes.

4.1.5. Comparison of different models

Morris (1982) described three models of the European Hydrological System. These snow melt models are based on (1) a degree-day factor, (2) the energy budget method and (3) full solutions of the equations of flow of mass and energy in snowpack (the fully distributed
model). Sensitivity of these models to their parameter values was tested. The models were implemented in two sites: in the sub-Arctic area of the Cairngorm mountains in Scotland and in a high-Alpine area in Switzerland. The third model was found to provide the best prediction of snow depth in the region under consideration.

Several publications have been devoted to comparison of different methods. Braun and Lang (1986) performed test runs on several snow runoff models for a range of Alpine catchments with area from 3.2 km\(^2\) to 1696 km\(^2\). They used an empirical ‘temperature index’ method and a ‘temperature and wind index’ method, a ‘combination’ and ‘extended combination’ method and a physically based ‘energy balance’ approach. They found that in small and medium catchments the advanced techniques gave an improvement, compared with the simple ‘temperature index’ method, whereas for the big catchments (with area > 1000 km\(^2\)) such improvement can be obtained only for years with an anomalously high level of snowpack. They concluded that the choice of particular runoff model may influence the quality of prediction more than the choice of particular snow melt/formation model. Also the choice of a more advanced snow model may affect the results less than the more detailed subdivision of the watershed considered into spatial subregions. Vehvilainen (1986) analysed three different models for prediction of snowmelt runoff in Finland and found that there were no significant differences in the results of applying (1) degree-day method, (2) combined degree-day method and (3) energy-balance method.

An intercomparison of 11 models of snowmelt runoff was performed by WMO (1986). The models were tested using data sets from six catchments with areas from 8.4 km\(^2\) to 2170 km\(^2\). Nine statistical characteristics were used for comparing the performance of these models. Several recommendations related to optimisation technique and verification methods were made for future development of such models. The need to include explicit equations for the modelling of soil moisture effects (the effect of frozen soil, especially) and to subdivide river
Basins into elevation zones in the mountainous regions, where the gradients of temperature and precipitation are strongly dependent on the altitude, were emphasised.

An overview of different techniques for prediction of melting runoff from glacierised areas was presented by Fountain and Tangborn (1985). The results of 7 models for predicting snow runoff were compared using graphical representation and the coefficient of determination or efficiency statistics. The common disadvantage of all techniques reviewed was the difficulty in predicting peak flows.

Bengtsson (1986) conducted a comparison of different types of snowmelt runoff model in order to establish the most appropriate model for a range of catchment sizes and modelling purposes. He concluded that physically based models are more appropriate for modelling surface runoff whereas the degree-day approach is more applicable for groundwater and subsurface runoff in large catchments.

4.1.6. Water equivalent of snow

The key problem of snow modelling is that often only snow depth data are available for the region under study, whereas a model typically required parameters describing snow water equivalent (SWE). The empirical equation for estimating water equivalent in snowpack using its depth measurement was provided by Logan (1973). For a range of elevation zones a set of regression relationships was established between the snowpack density and logarithm-transformed snowpack depth. Several meteorological parameters (rainfall, temperature and barometric pressure) were also considered as an additional influence on the snowpack density and were involved in this regression analysis. Empirical regressive relationships were declared applicable for estimating water equivalent in areas with elevation and climatic conditions similar to those where these relationships were established.
Rockwood (1973) was one of the first to use the calculation of SWE to forecast peak streamflow. He suggested the ‘thermal budget’ approach for prediction of flood events. Braun (1991) presented an overview of contemporary methods for estimation of SWE. He outlined methods of measurement of snow density, areal variability of snow pack and methods of verification of SWE modelling.

Day (1990) describes the spatially distributed snow accumulation and ablation model developed in the National Weather Service, USA, which allows integrated SWE for snow-affected catchments to be obtained in order to maintain hydrological models for stream discharge prediction and flood forecasting. Carroll et al. (1995) developed the system allowing incorporation in this model of airborne as well as ground-based data for more precise estimates of integrated SWE.

Snow effects are considerably important for Japan, where snowfalls provide from 30% to 50% of annual precipitation in the snowy regions. The modelling of all hydrological steps from SWE calculation to snow runoff modelling was performed by Koike et al. (1986, 1987) and Koike and Takahasi (1989). Three submodels were developed: (1) a submodel for calculating Basin-wide SWE, (2) a submodel for calculating snowmelt rate over the whole Basin and (3) a distributed runoff model based on the kinematic wave equation taking into account the channel network in the Basin. The Basin-wide SWE was calculated using the altitudinal distribution of SWE, which was approximated by a linear function of elevation. The snowmelt submodel has three components: (a) net radiation, expressed empirically through an insolation coefficient and mean daytime temperature, (b) a convection module based on a temperature index approach with a one-hour timestep (degree-hour factor) and (c) a condensation and rain melt module for rainy periods. Correction of the insolation coefficient in the snowmelt module was made to take into account the effects of local topography and
canopy, especially for forested areas. The model gave good results for runoff prediction in the Syozawa Basin (the upper Tone River).

4.1.7 Snow modelling in Australia and New Zealand

A water-balance method was applied by Fitzharris and Grimmond (1982) in order to compute seasonal snow storage in the mountainous Fraser catchment (120 km$^2$) in the South Island of New Zealand. The water-balance was calculated using monthly means over the period 1969-1978. Amount of equivalent melt water was calculated on a monthly basis. The mean snow storage calculated over 10 years was assessed as one third of mean annual flow.

Moore and Owens (1984a) designed a simple snow accumulation/melt model using daily observations of minimum and maximum temperature and precipitation. The advantage of this model was that it used only these meteorological data. Such an approach is especially important for New Zealand where the snow is measured at only a few sites. The meteorological data were recorded at two stations. Temperatures from both stations were extrapolated to every site in the area under consideration using the assumption that temperature decreases 6.5° per 1000 m of elevation. Precipitation was extrapolated to other elevation zones by multiplying by a constant correction factor, allowing the increase with altitude. The model was calibrated and tested for the alpine region of Craigieburn Range in the South Island of New Zealand. The model used a degree-day approach with a base temperature $T_b = 0$. The model has 5 parameters: a precipitation correction factor, threshold temperature (threshold above which the precipitation is treated as rain), degree-day factor, freezing coefficient and water retention capacity. The model was calibrated using a simple optimisation procedure, when a range of values for each parameter with small step size was checked in order to obtain the best fit for the measured snowpack. The parameters found for the calibration period 1967-68 were then applied for the simulation
of snowmelt over the period 1969-73. The performance of the algorithm provided a good approximation when temperature was taken from the upper station with elevation higher than the snow-line. The conceptual snow runoff module used was described in Moore and Owens (1984b). The Swedish HBV-3 model was selected for runoff modelling of the Camp Stream catchments in the Craigieburn Range. A snowmelt/accumulation module was based on an index of the strength of regional airflow. Snowmelt calculated by this module was integrated with liquid precipitation and used as an input for the runoff model. The results obtained demonstrated a better fit to the observed data than a simple degree-day model.

The snow fields in Australia are predominantly restricted to a mountainous area in the southeast of the continent: in the Snowy Mountains and Victorian alpine region. Despite this restriction, snow processes are very important for Australian hydrology because the Murray, Murrumbidgee and Snowy Rivers, having headwaters in these regions, play a crucial role in water supply in the country. Australian snowfields are not as extensive as those of Switzerland as claimed by Neal (1963). However, they are not inconsiderable and on average some 600 km² are snow-covered for at least ninety days per year (Slatyer et al., 1985). One of the main features of Australian snow hydrology is that spring floods do not appear regularly at the same time of the year; accumulation and melting can occur at any time in the autumn-winter period.

A model to predict the duration of the snow season, mean maximum snowpack depth and SWE, using the mean monthly characteristics of precipitation and temperature, was constructed by Galloway (1986, 1988). This model was developed for the thesis, in order to design a daily snow runoff model applicable to the Rivers of the Victorian alpine region and the Snowy Mountains. Whetton et al. (1996) and Haylock et al. (1994) continued this approach in order to investigate the possible climate impact on snow field size and snow season duration in the mountainous regions of Australia. They combined Galloway's model
with an interpolated high resolution interannual climate data set for the Victorian alpine region, in order to provide a snow season duration model for each gridcell in the region under consideration.

4.1.8. The context

The present work was undertaken as part of a general project to estimate climate impact on water availability and extreme events, such as droughts and floods, in the south-eastern Basins of the Murray-Darling Drainage Division. Modelling of streamflow in the Goulburn and Ovens Basins of this Division was reported in Chapter 2 (Schreider et al., 1996a,b). These Basins could be considered relatively snow-free. The snow-affected Basin of the Kiewa River and the western part of the Upper Murray Basin are considered in the present work. The spatially distributed empirical snow melt/accumulation model, based on a modified degree-day method, was applied in order to provide an input (equivalent rainfall) for the conceptual rainfall-runoff model, IHACRES.

4.2. Description of the Catchments

The Kiewa and Mitta-Mitta rivers of the mountainous area of eastern Victoria (Victorian Alps) were selected to calibrate and validate the snow runoff model. The Kiewa Basin (Figure 4.1) is located in the Eastern part of the Murray Darling Drainage Division (MDDD) between the Basins of the Ovens to the west and the Upper Murray River to its east. This Basin is the second smallest in the MDDD, with a total drainage area of 1,985 km². The part of the Basin considered in this work, above the streamgauging station at Mongans Bridge, has an area of 552 km². Mean annual discharge of the Basin is 705,000 ML or 3.2% of the total discharge of the state of Victoria (Water Victoria, 1989). Mean annual discharge at the Mongans Bridge station (N 402203) is 508,000 ML (Victoria Surface Water Information, 1984), which constitutes 70% of the total discharge of the Basin. This amount of water is comparable, for
example, with the average annual discharge of the Namoi Basin, in the northern part of MDDD, which has an area (43,000 km$^2$) 20 times larger than that of the Kiewa Basin. Of all the Murray tributaries the Kiewa River contributes the highest runoff per unit area. The headwaters of the Kiewa River are on the plateau of the Bogong High Plains in the southern part of the Basin. The east and west branches flow almost parallel to one other, then merge together downstream of the Mt. Beauty station (83023). The major tributary of the Kiewa river in this area is Mountain Creek which flows down a small plateau near Mt. Bogong - the highest point in the Basin with elevation 1,986 m. Below the Mt. Beauty station the Kiewa River flows almost directly north taking two tributaries, Yackandandah and Middle Creeks, until it joins the Murray River east of Wodonga city below Lake Hume.

Climatology and physiography vary across the Kiewa Basin. Mean annual precipitation increases from about 700 mm near Wodonga in the north to 1,700 mm at Tawonga. It is 1,880 mm at Bogong Village and 2,430 mm at the Bogong High Plains in the southern mountainous part of the Basin near the Great Dividing Ridge (Water Victoria, 1989). Some 23% of the Basin has elevation higher than 900 m and this area provides 52% of the Basin yield. Almost all winter precipitation over the area with elevation higher than 1,400 m falls as snow. The streamflow regime in the Basin has very distinct seasonal variations. The August-October flow yields more than 50% of annual discharge whereas the January-March flow provides only 7% of the annual amount of water.

Several small artificial reservoirs are located in the upper part of the Kiewa Basin. These operate for hydroelectric power generation. The Rocky Valley Storage has the largest capacity of 28,400 ML. Modification of the natural regime of the Kiewa River produced by these artificially regulated reservoirs is negligibly small, compared with its total discharge, even in the summer period. Total water use within the Basin of 13,160 ML is relatively small, with irrigation consumption constituting 6,190 ML per year or 47% of total water use.
Figure 4.1. River network, meteorological and discharge stations for the catchments under consideration in the Kiewa Basin and the Mitta-Mitta catchment of the Upper Murray Basin.
The Upper Murray Basin is located east of the Kiewa Basin. Its total area of 1,528 km² is in both states of New South Wales and Victoria. This Basin is especially important for water supply in the state of Victoria because two of the three largest Victorian reservoirs are located there. Lake Hume with a capacity of 3,038,000 ML is located in the lower part of the Basin on its north-western edge. The Victorian section of this Basin (Figure 4.1) with total area of 1,000 km² comprises the Mitta-Mitta catchment and borders the left bank of the Upper Murray River. The total discharge provided from the Upper Murray Basin is 3,920,000 ML per year, including 580,000 ML per year which is exported from the Snowy River Basin via the Snowy Mountain Hydroelectric Scheme to the New South Wales part of the Basin. This amount of water is shared equally between Victoria and New South Wales. The Mitta-Mitta catchment, considered in the present work, provides about half of the total discharge of the Victorian section of the Basin. Mean annual flow at its lowest station, Tallangatta, is 1,420,000 ML. The largest reservoir in Victoria, with about 4,000,000 ML capacity, Lake Dartmouth, is located in the middle of the Mitta-Mitta catchment. That part of the river located upstream of this reservoir was chosen for modelling streamflow. Although there is some agriculture in the lower valleys of the Basin and some cattle stations in its upper part, about 80% of its area is still forested. Water use in the Basin is very restricted, only 4,830 ML per year, which are provided almost completely from surface water; and 75% of this consumption is used for irrigation.

The climatology of this Basin is also very heterogeneous and topography strongly influences spatial variations in the climate. Average annual precipitation reduces with decreasing elevation, from more than 2,400 mm per year at Mt Bogong on the border with the Kiewa Basin to about 700 mm in the northern part of the Basin along the Murray River. The relatively highly located Omeo-Benambra area is shadowed from prevailing westerly air streams by the Bogong High Plains and the mean annual precipitation is lower at about 700
Snow provides a considerable amount of water to the Basin: the high flow in October is attributed to melting snow in its upper area.

The Hinnomunjie catchment of the Mitta-Mitta River is located in the south-western part of the Upper Murray Basin. The area of the catchment considered (above streamgaging station 401203) is 1,533 km². The main tributaries of the Mitta-Mitta River in this catchment are the Big, Bundara and Cobungra Rivers in the north-western part of the catchment and Livingstone Creek in its southern part.

The headwaters of both catchments selected for modelling runoff are in the Bogong High Plains area. A description of the natural environment of this region, land use history and the effect of these land uses is presented in Lawrence (1994), where a complete list of relevant references including technical reports and unpublished manuscripts can be found. The geological structure of the plateau is represented by basalts, gravels and alluvium. The most typical soils in this area are shallow organic loam and alpine humus soil. The property of the shallow organic loams, significant for runoff modelling, is that their infiltration capacity is higher under moist rather than dry conditions. Undifferentiated stony loams are the most common type of soil on ridge tops and steep slopes. The vegetation of the plateau is very diverse with a prevalence of Snow Gum Eucalyptus in forested areas and various snow grasses in the grasslands, traditionally used as pasture areas. The tourist industry, skiing especially, is widely developed in this region.

Information on catchment areas, mean annual discharges and the length of continuous streamflow records is summarised in Table 4.1.
Table 4.1. The catchments under consideration (Victorian Surface Water Information, 1984)

<table>
<thead>
<tr>
<th>Station number</th>
<th>River and station location</th>
<th>Mean annual discharge (ML)</th>
<th>Area (km²)</th>
<th>Commencement of continuous streamflow records</th>
</tr>
</thead>
<tbody>
<tr>
<td>402203</td>
<td>Kiewa River at Mongans Bridge</td>
<td>508,000</td>
<td>552</td>
<td>1955</td>
</tr>
<tr>
<td>401203</td>
<td>Mitta-Mitta River at Hinnomunjie</td>
<td>475,000</td>
<td>1533</td>
<td>1970</td>
</tr>
</tbody>
</table>

4.3. The climatological data

A common approach in calculation of meteorological data for input to spatially distributed snow melt/accumulation modelling is a recalculation of data recorded at several adjacent stations according to elevation (Bloeschl, 1991). For the present work, however, the results obtained by Hutchinson (1989, 1991) and Hutchinson and Dowling (1991) for spatial interpolation of climate data for the Australian region are used. Hutchinson (1989) developed an algorithm which interpolates climate data between stations using a polynomial spline surface fitting procedure and topographical data with a resolution of 1/40th of a degree or about 2.5 km. The algorithm was used by Whetton et al. (1996) and Haylock et al. (1994) to spatially interpolate monthly means of climate data for the entire Australian continent. This method allows one to obtain elevation-dependent long term monthly means of minimum, maximum and mean daily temperatures and precipitation for the region under consideration with the resolution mentioned above. These data were used by Haylock et al. (1994) for modelling duration of the snow season. Long-term means were calculated for the alpine region of Australia (from 145°30'E to 149°30'E and from 38°S to 35°S) for each month of the year using 49 temperature stations and 404 rainfall stations. The periods of data record for each station varied from 10 to 133 years.
The model described in the present work uses daily temperature and precipitation data as an input to the snow runoff model. Our procedure calculates daily meteorological data, based upon the relevant long term monthly interpolation, for each gridcell in the alpine region.

Precipitation was computed using an assumption that the ratio of long-term mean monthly precipitation, taken for each gridcell, to the mean monthly precipitation calculated for adjacent gauging stations (base stations) is equal to the ratio of rainfall on each particular day for this gridcell to rainfall measured on this day at the same base stations:

\[
r_k^{\text{int}}(i,j) = r_k(\text{station}) \cdot r_l^{\text{mean}}(i,j)/r_l^{\text{mean}}(\text{station}),
\]

where \( k \) indicates number of the day, \( r_k^{\text{int}}(i,j) \) is interpolated daily rainfall for the gridcell with coordinates \((i,j)\), \( r_k(\text{station}) \) is rainfall measured at the station on day \( k \), \( r_l^{\text{mean}}(i,j) \) - the long term mean rainfall for the month \( l \) \((l=1,2,...,12)\) calculated for this gridcell and \( r_l^{\text{mean}}(\text{station}) \) is this long term mean calculated for the site of the station location.

The interpolated daily temperature for each gridcell was calculated using an assumption that the difference between the daily temperature in each gridcell and the long term monthly mean value of temperature taken in this gridcell for this month is equal to the difference between the daily temperature measured at the adjacent station on this day and the long term mean value of temperature calculated for the gridcell where the station is located for this month:

\[
t_k^{\text{int}}(i,j) - t_l^{\text{mean}}(i,j) = t_k(\text{station}) - t_l^{\text{mean}}(\text{station}),
\]

where \( k \) is number of the day, \( t_k^{\text{int}}(i,j) \) is interpolated daily temperature for the gridcell with coordinates \((i,j)\), \( t_l^{\text{mean}}(i,j) \) is the long term mean temperature for the month \( l \) estimated for this gridcell, \( t_k(\text{station}) \) is temperature measured on the station at the day \( k \) and \( t_l^{\text{mean}}(\text{station}) \) indicates the long term mean temperature calculated for the station site. This interpolation procedure was applied to mean daily as well as to daily minimum temperatures.
An important assumption of this method is that the number of rain days is the same throughout the catchment, whereas it is possible that there are more rainy days at sites which are wetter than the selected base station and vice versa. Also, the climatological lapse rate (for temperature) is assumed to apply on all days. In reality this may vary considerably from day to day and may be correlated with precipitation occurrence.

The question arises as to how sensitive are the results of interpolation to the choice of particular rainfall or temperature station. Four rainfall stations were selected in the region under consideration. These are Tawonga (number 83038, elevation 314 m), Omeo (83025, 649 m), Rocky Valley (83043, 1652 m), Benambra (83003, 715 m) and Mt Beauty (83023, 366 m). Minimum and mean daily temperature (mean arithmetic value of daily minimum and maximum temperature) was taken from the Mt Beauty station, chosen as a base for the interpolation procedure. Temperature was also recorded at the Omeo station, which was also used for testing the sensitivity of the interpolation procedure.

Figure 4.2 shows how sensitive the interpolation procedure is to the station chosen as the base for the algorithm described above. Annual precipitation was compared for the measured data at Omeo (a), Tawonga (b), and Rocky Valley (c) with the interpolation results obtained for their sites when the base station for the interpolation procedure was the Mt Beauty meteorological station. The annual measured data and interpolated rainfall presented in Figure 4.2 show a reasonable fit of interpolated and measured data. A difference between interpolated and measured data for Rocky Valley station in 1971 explained by lack of data in the recorded rainfall in that year. The difference between measured and interpolated monthly data is shown in Figure 4.3 for Benambra station (a) and Omeo (b). The interpolation results are good for the Benambra station and may be considered reasonable enough even for the Omeo station sites, although it is located far from the base station Mt Beauty.
Figure 4.2a. Annual measured (solid line) and interpolated rainfall (dashed line) for the Omeo, for the period 1965-84.
Figure 4.2b. Annual measured (solid line) and interpolated rainfall (dashed line) for the Tawonga station for the period 1965-84.
Figure 4.2c. Annual measured (solid line) and interpolated rainfall (dashed line) for the Rocky Valley station for the period 1965-84.
4.4. The model description

4.4.1. Snow melt/accumulation module

The snow melt/accumulation module for modelling daily processes is based on modification of the empirical degree-day approach developed by Whetton et al. (1996) for modelling snow melt/accumulation on a monthly timestep. The main advantage of the suggested approach is that it does not require any input data except daily temperature and precipitation, which is useful for modelling of snow processes in regions with a lack of regular snow observations. The algorithm allows modelling of intermediate hydrological parameters such as snow depth, accumulation and ablation for all periods of the annual cycle without resource to any additional observations. However, note that the main task of the method developed was to improve the precision of runoff modelling in snow-affected catchments, and not to provide an accurate prediction of snow cover distribution.

Several factors which influence snow processes are not considered here. Among such factors the most important are topography and vegetation. The elevation of every grid cell of the catchments is the only topographical information used in the model; the degree of inclination of slopes and their spatial orientation were not taken into consideration. Neither was vegetation cover included in any way. Such a level of simplification does not ensure high accuracy in the spatial modelling of snow depth, but can provide an accurate integral value of the amount of melted water or precipitation accumulated as snow.

The states of the snow module, calculated for every \( i \)-th day, are:

\[ A(i) \] - daily accumulation (mm of water),

\[ M(i) \] - daily ablation (mm of water),

\[ M_p(i) \] - daily potential ablation (mm of water),
Figure 4.3a. An example of monthly measured (solid line) and interpolated (dashed line) rainfall for the Benambra station.
Figure 4.3b. An example of monthly measured (solid line) and interpolated (dashed line) rainfall for the Omeo station.
$D(i)$ - snow water equivalent at day $i$ in mm,

$p(i)$ - daily precipitation in mm interpolated for the modelling site,

$t_{av}(i)$, $t_{min}(i)$ - daily average and minimum temperature (mean arithmetic value of minimum and maximum temperature), interpolated for this site and

$r_{eqv}(i)$ - daily equivalent rainfall.

The daily accumulation is calculated according to:

$$A(i) = p(i) P_s(t_{min}(i)),$$

where $P_s(t_{min}(i))$ is the probability of precipitation falling as snow as a function of daily minimum temperature. The function $P_s(t_{min}(i))$ was established empirically by Ruddell et al. (1990) for high elevation localities in the Australian alpine area (Falls Creek, Mt Hotham, Hotham Heights, Mt Buffalo, Mt Buller, Bogong Village, Perisher and Cabramurra) on the basis of 16,000 days of temperature and precipitation observations (Figure 4.4).

The daily potential ablation is calculated as a product:

$$M_p(i) = 2.9 T Af(month, t_{month}),$$

where $T$ is a mean daily temperature ($t_{av}(i)$) in degrees Celsius, if it is greater than zero Celsius, and 0, if it less than zero (analogue of relationship (4.1) with $T_b = 0$). The degree-day factor 2.9 mm°Cxday was established empirically (Whetton et al., 1996) for the Victorian alpine region using snow data from the Spencer Creek station and it agrees well with the value 3.2 mm°Cxday provided by Todd (1970). $Af(month, t_{month})$ is the albedo factor computed for each month of the year as a function of mean monthly temperature $t_{month}$. This function is also established empirically and its values were tabulated by Galloway (see Whetton et al., 1996) as follows:
Figure 4.4. The probability that precipitation will fall as snow for the Victorian alpine region (from Ruddell et al., 1990).
\[ Af = \frac{t_{\text{month}}}{12} + \frac{7}{6}, \text{ for March, April and May} \]

\[ Af = \frac{t_{\text{month}}}{24} + \frac{12}{13}, \text{ for June, July and August} \]

\[ Af = \frac{t_{\text{month}}}{8} + \frac{5}{4}, \text{ for other months of the year} \]

If \( t_{\text{month}} \) is less than \(-2^\circ \text{C} \), then \( Af \) is assumed to be equal to 1.

The significant difference between this approach and usual degree-day models is that the processes of accumulation and melt were assumed fuzzy: there is no strict temperature threshold strictly dividing ablation (if temperature is higher than this threshold), and formation of snow (if it is less then this threshold).

Equivalent daily snow depth for each gridcell is calculated as a sum of snow depth in the previous day and daily accumulation minus daily ablation:

\[ D(i) = D(i-1) + A(i) - M_p(i), \quad (4.2) \]

or is zero if \( M_p(i) \) is greater than the sum \( D(i-1) + A(i) \).

The equivalent snow water value allows definition of the daily ablation. It is equal to potential ablation if equivalent on the previous day is greater than potential ablation, and equivalent on the previous day if this value is less than potential ablation (amount of melted water cannot exceed amount of water equivalent in the snow cover):

\[ M(i) = M_p(i), \text{ if } M_p(i) < D(i-1) \]

\[ M(i) = D(i-1), \text{ if } M_p(i) \geq D(i-1) \]

The model output is the daily equivalent rainfall calculated for each gridcell of the catchments under consideration as the sum of measured daily precipitation and snowmelt minus daily accumulation:
\[ r_{eq}(i) = p(i) + M(i) - A(i) \]

The equivalent rainfall calculated for each gridcell is integrated over the whole catchment by computing the spatial mean arithmetic value. The daily integrated equivalent rainfall is used then as an input for the conceptual rainfall-runoff model.

4.4.2. Summary of the general procedure

The algorithm of snow runoff modelling can be summarised step-by-step as follows (See the schematic diagram in Figure 4.5):

1. Interpolation of daily climate data (precipitation, minimum and maximum temperature) for each gridcell (2.5 km x 2.5 km, here) of the catchment under consideration.

2. Application of empirical degree-day snow melt/accumulation model to each gridcell in order to calculate the equivalent amount of water.

3. The calculation of integral equivalent rainfall and temperature over the whole catchment by computing the average value of equivalent rainfall and temperature using the data for every gridcell.

4. Implementation of the conceptual rainfall-runoff model IHACRES for modelling the snow runoff on a daily basis. This model also has two modules:

   (a) a non-linear module for transformation of equivalent rainfall into excess rainfall

   and

   (b) a linear module for calculation of daily runoff using the antecedent values of streamflow and excess rainfall.
Interpolation of meteorological data

The application of the snow melt/accumulation procedure in each gridcell of the catchment

Integration of the equivalent rainfall and temperature over entire catchment

The conceptual rainfall-runoff model – IHACRES

Non-linear module
Excess rainfall
Linear module

Modelled streamflow

Figure 4.5. The diagram illustrating the algorithm of snow runoff modelling.
4.5. Results of the snowmelt/accumulation and streamflow modelling

4.5.1. Snow melt/accumulation modelling

One of the main criteria for verification of the model described is the fit of modelled streamflow to its measured value. However some interim results of the snow modelling can be used for additional assessment of the model quality. Figure 4.6 shows the long term means of monthly streamflow for the Mitta-Mitta River, of measured precipitation (interpolated over the Mitta-Mitta catchment) and of the monthly equivalent rainfall, obtained as a result of application of the snow melt/accumulation model. The typical period of snow accumulation during June, July and August and the typical melt season during September, October and November are clearly displayed in this figure. The peak value of streamflow also corresponds more closely to the peak value of the equivalent rather than measured rainfall. The melt and accumulation periods (this does not mean that only this process takes place at this period but it prevails) are demonstrated in Figure 4.7 for the (a) Rocky Valley and (b) Tawonga stations, where the monthly interpolated precipitation and equivalent rainfall are shown as a function of time. The values of these two characteristics are equal in the summer period, the equivalent rainfall is less than measured precipitation values in the accumulation period (June-August) and higher during the melt season (September-November). The snow melt/accumulation processes are very considerable at sites with high elevation such as the Rocky Valley station (Figure 4.7a) and not so important at the lower sites such as the Tawonga station (Figure 4.7b).

The snow melt/accumulation model also outputs equivalent snow depth in mm of water (in other words, water equivalent of snow pack) and duration of the snow season. The latter is defined in the model as the longest period over which snow depth \( D(i) \), defined by formula
Figure 4.6. Long term mean values of monthly streamflow of the Mitta-Mitta River (circles), of measured precipitation interpolated over the Mitta-Mitta catchment (diamonds), and of monthly equivalent rainfall, obtained from the snow melt/accumulation model (triangle).
Figure 4.7a. Measured (solid line) and equivalent (dashed line) rainfall for the Rocky Valley station (elevation 1652 m a.s.l), where snow melt/accumulation processes are substantial.
Figure 4.7b. Measured (solid line) and equivalent (dashed line) rainfall for the Tawonga station with low elevation 314 m a.s.l., where snow melt/accumulation processes are almost negligible.
(4.2), is greater than zero. A few snow depth observations are available for the region under study and it is possible to compare the observed and independently modelled values of snow depth. Ruddell et al. (1990) provide snow depth observations, measured terms of its water equivalent (mm), for several sites in the Australian alpine region. Figure 4.8 shows the observed cumulative water equivalent of snowpack recorded at the Falls Creek area located in the Kiewa River catchment and our modelled value of this variable. The modelled duration of the snow season corresponds quite well with the observed data. The annual maximum snow depth (in mm of water) observed for the Rocky Valley station was compared with the modelled values at this site. Figure 4.9 demonstrates that the general pattern of observed and modelled values have much in common.

4.5.2 Results of snow runoff modelling

Model calibration for the snow-affected Mitta-Mitta and Kiewa catchment was performed with daily time series of:

1. the equivalent rainfall, estimated by the snow melt/accumulation module,

2. temperature, interpolated for each grid cell of the catchment and then integrated over this catchment, and

3. streamflow during the period 1965-1984, recorded at the Hinnomunjie station (401203) for the Mitta-Mitta River and at the Mongans Bridge station (402203) for the Kiewa River.

The period has been divided into 9 calibration periods (CP) each with a duration of about two years. The selected CP’s do not overlap substantially. Successful calibrations were obtained for each of these two catchments. The calibration results, in terms of model efficiency, are summarised in Table 4.2. Examples of the model fit to the observed daily streamflow for the Kiewa and Mitta-Mitta Rivers for CP 8 are shown in Figure 4.10.
Figure 4.8. Observed and modelled snow depth for the Falls Creek station at 1984.
Figure 4.9. Observed and modelled maximum snow depth at the Rocky Valley Station for the period 1965-1984.
Table 4.2. Model efficiency values $E$ for calibration of the snow runoff model for the Kiewa and Mitta-Mitta catchments.

<table>
<thead>
<tr>
<th>Catchment and station number CP</th>
<th>The Kiewa River 402203</th>
<th>The Mitta-Mitta River 401203</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 4/02/66- 3/02/68</td>
<td>0.835</td>
<td>0.827</td>
</tr>
<tr>
<td>2 5/01/68- 4/01/70</td>
<td>0.804</td>
<td>-</td>
</tr>
<tr>
<td>3 23/02/70-22/02/72</td>
<td>0.807</td>
<td>0.718</td>
</tr>
<tr>
<td>4 24/03/72-23/03/74</td>
<td>0.844</td>
<td>0.848</td>
</tr>
<tr>
<td>5 14/03/74-13/03/76</td>
<td>0.848</td>
<td>-</td>
</tr>
<tr>
<td>6 2/02/76- 1/02/78</td>
<td>-</td>
<td>0.727</td>
</tr>
<tr>
<td>7 2/02/78- 1/02/80</td>
<td>0.846</td>
<td>-</td>
</tr>
<tr>
<td>8 11/02/80-10/02/82</td>
<td>0.884</td>
<td>0.859</td>
</tr>
<tr>
<td>9 10/02/82- 9/02/84</td>
<td>0.836</td>
<td>0.910</td>
</tr>
</tbody>
</table>

- denotes model's poor performance ($E < 0.700$).

The consistency of the results obtained was checked by simulation runs performed over the whole 19 year period of observation available (1965-1984) with each of the calibrated models. Thus, the values of the parameters $\tau_w$, $f$, $c$, and the coefficients in the linear combination (2.2), optimised during the calibration runs, were used for modelling the streamflow using the equivalent rainfall and temperature series for the whole 19-year period. The efficiency statistic $E$ and mean daily bias (absolute error in cubic meters per second, cumeecs) for these simulation tests are shown in Table 4.3. The calibration mode results described above show that the IHACRES model, when applied to the snow-affected catchment in combination with the snow melt/accumulation module provides the results of about the same quality level as obtained in snow free Basins; see Chapter 2 where the results of the IHACRES model application to the snow-free Goulburn and Ovens Basins
Figure 4.10a. Observed (solid line), modelled (dashed line) streamflow (cumecs) and error for calibration period 8 (1980-1982) for the Kiewa catchments.
Figure 4.10b. Observed (solid line), modelled (dashed line) streamflow (cumecs) and error for calibration period 8 (1980-1982) for the Mitta-Mitta catchment.
are described. The results obtained for the Kiewa River are consistently better than for Mitta-Mitta. One possible explanation is that the Mitta-Mitta catchment, which is almost three times the size of Kiewa, much more heterogeneous relief and vegetation structure.

Table 4.3. Simulation with nine two year calibrated models over whole period of observation for the Kiewa and Mitta-Mitta catchments. $E$ and Bias (mean daily error in cumecs). Bold values denote the best selected model.

<table>
<thead>
<tr>
<th>Catchment and station number</th>
<th>The Kiewa River</th>
<th>The Mitta-Mitta River</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model number</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.767 1.11</td>
<td>0.627 0.13</td>
</tr>
<tr>
<td>2</td>
<td>0.811 0.28</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>0.767 -0.49</td>
<td>0.649 -0.76</td>
</tr>
<tr>
<td>4</td>
<td>0.756 -1.44</td>
<td>0.669 0.50</td>
</tr>
<tr>
<td>5</td>
<td>0.801 0.22</td>
<td>-</td>
</tr>
<tr>
<td>6</td>
<td>0.756 -1.77</td>
<td>-</td>
</tr>
<tr>
<td>7</td>
<td>0.788 0.99</td>
<td>-</td>
</tr>
<tr>
<td>8</td>
<td>0.745 4.21</td>
<td>0.605 4.13</td>
</tr>
<tr>
<td>9</td>
<td>0.799 1.44</td>
<td>0.681 0.87</td>
</tr>
</tbody>
</table>

- denotes model's poor performance for this calibration period (c.f. Table 4.2)

The simulation results of the Kiewa River streamflow for the 19-year period are presented in Figure 4.11 for (a) annual flow, (b) for July flow, when the accumulation processes prevail, and (c) for October flow (the month with an extensive melt). The mean relative error, calculated for 5-year running mean values of modelled and observed flow is equal to 0.07. The long term simulation results obtained for the snow-affected Kiewa catchment
Figure 4.11a. Simulation over 19-year period for the model calibrated on CP2 (Table 4.2) and long term historical climatological data for the Kiewa catchment. Mean values for precipitation (above), temperature (middle) and the observed and modelled flow (below) are shown for the annual data.
Figure 4.11b. Simulation over 19-year period (1965-1984) for the model calibrated on CP2 (Table 4.2) and long term historical climatological data for the Kiewa catchment. Mean values for precipitation (above), temperature (middle) and the observed and modelled flow (below) are shown for July, when accumulation prevails.
Figure 4.11c. Simulation over 19-year period (1965-1984) for the model calibrated on CP2 (Table 4.2) and long term historical climatological data for the Kiewa catchment. Mean values for precipitation (above), temperature (middle) and the observed and modelled flow (below) are shown for October, when snowmelt prevails.
are also of the same quality as corresponding results for the snow-free catchments of the Goulburn and Ovens Basins, where these errors are 0.05 - 0.08. However for the Mitta-Mitta catchment the corresponding long term simulation errors are 0.12.

4.6. Conclusions

The problem of snow runoff modelling was considered for catchments in the Australian alpine region. A snow melt/accumulation model was adapted and developed to provide an equivalent rainfall input for the conceptual streamflow model IHACRES which was used for subsequent runoff modelling. The snow melt/accumulation model is based on a modified degree-day approach. The model provides the equivalent amount of melted/accumulated water for each gridcell of the catchments under consideration with a spatial resolution of 2.5 km x 2.5 km. The method allows modelling of the melt/accumulation processes directly without recourse to information about current snow cover distribution in the area, which is especially advantageous for regions with a lack of observational snow data.

Successful application of the conceptual rainfall-runoff model IHACRES was performed for the Mitta-Mitta and Kiewa Rivers where the IHACRES model was applied for the first time on a snow-affected area. The calibration results obtained for 9 two-year non-overlapping periods show that the model performs with about the same efficiency for snow-affected as for snow-free Basins in the region. The model was tested by simulation over the 19 year period of observation for both catchments under consideration. The results of this test showed that the models obtained for the Kiewa Basin approximate observed streamflow with the same volumetric error as for neighbouring snow-free catchments of the Goulburn and Ovens Rivers. The larger errors obtained for the Mitta-Mitta catchment are possibly due to higher heterogeneity of its landscape and vegetation structure.

The model is to be used subsequently to model potential climate impacts on water availability and extreme flow events such as floods and droughts with an assumption that the vegetation conditions in the region will remain stable.
CHAPTER 5

COMPARATIVE ANALYSIS OF CLIMATE IMPACT ON WATER AVAILABILITY AND EXTREME EVENTS FOR SNOW-FREE AND SNOW-AFFECTED CATCHMENTS OF THE SOUTHERN MURRAY-DARLING BASIN

Summary

This chapter reports on the comparative analysis of possible climate change impacts on water availability in snow-free and snow-affected Basins in our study region, which was selected because of its importance to water supply for Australian rural industry. It includes the Goulburn, Ovens and Kiewa Basins and the Victorian part of the Upper Murray Basin. Possible climate impacts for the snow-free Goulburn and Ovens Basins were studied in Chapter 3. Climate impacts on the snow-affected Kiewa and Mitta-Mitta catchments are analysed in this Chapter and a comparison of impacts for both types of Basins is also undertaken.

The conceptual rainfall-runoff model IHACRES was successfully calibrated and validated for a snow-free region (the Goulburn and Ovens Basins) as well as for snow affected regions (the Kiewa Basin and Mitta-Mitta catchment in the Upper Murray Basin) in Chapter 4. In the latter case, an empirical snow melt/accumulation model, based on a modified degree-day approach, was developed and applied in order to calculate snow melt excess and snow...
accumulation for conversion into equivalent rainfall, which was used as an input into the IHACRES model. Climate scenarios developed by scientists from the Division of Atmospheric Research CSIRO were applied for transforming historical climate data that were relevant for the years 2030 and 2070. Estimates of streamflow changes for these climate scenarios were obtained for these periods for all Basins under consideration.

Climate impacts were considered from two perspectives: impacts on annual and monthly discharge in the Basins, and impacts on the probability of extreme events such as floods and droughts. As the scenarios provide a range of possible changes in broad climatic factors, average temperature and precipitation, two extreme cases were considered: 'most dry' and 'most wet' climatic changes for both future dates (2030 and 2070). A considerable reduction in the available water supply was found for the case of the 'most dry' (pessimistic) scenarios in both snow-free and snow affected regions: a streamflow volume reduction of 28% - 38% for 2030 and 53% - 64% for 2070 is simulated, depending on the catchment considered. The amount of available water decreases more in snow-free catchments than in the snowy area, although this difference is small. The 'most wet' (optimistic) scenarios provide quite different impacts for snow-free and snow-affected catchments: these changes are negligibly small (between 3% reduction and 4% increase at 2030 and 0% - +6% at 2070) for the snow-free area, whereas they are considerably larger (7% - 11% increase at 2030 and 12% - 21% at 2070) depending on the catchment considered for snow-affected Basins.

For estimating the impact of climatic change on the probability of extreme events, the conclusion is that increases in the probabilities of high flow events in the future are about 50 ± 10% at 2030 and 100 ± 20% at 2070 for both types of catchments for the 'most wet' scenario. These probabilities are slightly higher for snow-affected regions.
The probability of high flow for the ‘most dry’ scenarios rapidly decreases for these two dates for both types of catchments. For the snow-affected Kiewa River catchment, drought frequency, as defined by a soil wetness index, increases 36% for the ‘dry’ scenario at 2030 and 87% for this scenario at 2070. These percentages are much the same for snow-free areas: a 35% and 80% increase, respectively.

5.1. Introduction

The results of calibration and validation of the IHACRES model in the Goulburn and Ovens Basins, considered as snow-free, to a first approximation, can be found in Chapter 2 (also Schreider et al., 1996a,b). Description of the snow melt/accumulation module and results of the snow runoff model calibration and simulation in the mountainous area of the Kiewa and Mitta-Mitta catchments were presented in Chapter 4 (also Schreider et al., 1996d).

The reliability of the selected model, illustrated by the results obtained in the Goulburn, Ovens, Kiewa and Mitta-Mitta catchments, allows its use for estimation of the possible climate change impacts on the water supply of this region under certain assumptions. These assumptions neglect changes in the overall nature of the Basins’ vegetation cover in terms of its response to precipitation and temperature. Evapotranspiration rates are considered to remain the same for a given input of precipitation and temperature. Climate scenarios developed in the Division of Atmospheric Research CSIRO (CIG, 1992; Whetton, 1993) were used to produce the daily precipitation and temperature time series relevant for climate at 2030 and 2070, from which the IHACRES model was used to calculate the changes in streamflow for these scenarios. The daily time series of climate data were generated by transforming historical series, by scaling precipitation and adding a constant to temperature. This involves the assumption that the frequency distribution of the scaled precipitation and transformed temperature remains the same as for the untransformed historical data.
Daily streamflow was estimated for the ‘most wet’ and ‘most dry’ scenarios for 2030 and 2070 respectively. Climate impacts were calculated for mean monthly and annual discharge in the region under consideration.

The potential impact of climate change on the frequency and magnitude of precipitation was studied in Fowler and Hennessy (1995). A list of relevant references concerning the problem of estimating possible climate change impacts on streamflow in snow-free catchments was provided in Chapter 3 (Schreider et al., 1996b). An overview of such publications is given in Gleick (1986, 1989), Dooge (1992), Leavesley (1994) and Morassutti (1992). Work related to the possible effects of global warming on snow-affected regions is discussed below. The literature with respect to this problem usually concerns glacierised Basins, where a huge amount of ice pack has accumulated over thousands of years, and the main consequence of warming is a dramatic increase in the melting of glaciers. The present work is related to the estimation of climatic impacts for Basins with seasonal snowpack.

Fukushima et al. (1991) investigated the effects of global warming on streamflow in the Langtang Valley in the Nepal Himalayas. This catchment of area 333 km² has 38 percent of its area covered by glaciers. River discharge was simulated by a conceptual streamflow forecasting model, HYCYMODEL, where the snowmelt module was based on an empirically established mass balance relationship. Streamflow doubled with a 2°C climate warming, if the glacierised area is presumed to remain constant, and only by 30% if the glacierised area is reduced to 30 percent of its total area. The problem of which meteorological factors most affect ice and snowmelt processes in different geographical regions and under different climate conditions was discussed in Aizen and Aizen (1993). They concluded that the major climatic influence for continental regions, where the share of the solar radiation is more than 90% of the total heat balance, is shortwave radiation, whereas for regions with strong oceanic...
influence, it is temperature. This conclusion accords with our choice of a degree-day approach for the snow melt/accumulation modelling in the present work.

Kuhn (1993) overviewed methods of determining the response of glaciers and seasonal snow cover to climate changes. He classified these methods into four groups: a search for analogous changes in the past, multivariate analysis of past data, deterministic models, and an inclusion of changes of climate in the input meteorological data. The last approach is used in the present work where the calculation of climatic time series (temperature and precipitation), was implemented using transformation of historical series from given long-term mean scenarios of possible climate changes.

5.2. The region under consideration

As indicated in earlier chapters, the Goulburn, Ovens, Kiewa and Upper Murray Basin of the Murray-Darling Drainage Division are located in the eastern part of the state of Victoria, Australia, and are important contributors to its water supply. The impacts of climate on water availability in this region are of interest for planning purposes; the water resources of the Goulburn Basin above provide approximately 40% of total irrigation water use in Victoria.

The three biggest water reservoirs of Victoria: the Dartmouth, Eildon and Hume Lakes with a total capacity over 7,000,000 ML are located in this area. Analysis of possible impacts was performed on five groups of catchments:

1. Catchments upstream of Lake Eildon in the Goulburn Basin (Figure 2.1a): the Big, Upper Goulburn, Jamieson and Delatite Rivers;

2. Catchments downstream of Lake Eildon (Figure 2.1a): the Rubicon, Acheron, Murrindindi and Yea Rivers and King Parrot Creek;
3. Catchments of the Ovens Basin (Figure 2.1b): the Upper Ovens, Buckland, Buffalo, Dandongadale and King Rivers;

4. The catchment of the Kiewa River at Mongans Bridge (Figure 4.1) and

5. The catchment of the Mitta-Mitta River at Hinnomunjie (Figure 4.1).

The total area of the catchments modelled is around 8,750 km$^2$ and the total mean annual discharge modelled exceeds 4,000,000 ML per year. A detailed description of the Basins under consideration and relevant references can be found in Chapters 2 and 4.

5.3. The climate scenarios and scaling of the climatic time series

Mean climate scenarios for the Australian region were described in CIG (1992) and Whetton (1993) and they are based on the scenarios of future global warming given by Wigley and Raper (1992). Their particular realisation for the Victorian alpine region was presented in Chapter 3. These scenarios developed for the Southern coastal region of Australia (less then 200 km from the coast) provide a warming in the year 2030 in the range 0.5$^\circ$ - 2.0$^\circ$ and in 2070 in the range 1.0$^\circ$ - 5.0$^\circ$. The rainfall change scenarios for the Victorian alpine region are 0 - +20% for the summer half-year (November-April) and -10% - +10% for the winter half-year (May-October) in 2030. In 2070 this change is 0 - +40% and -20 - +20% respectively. In order to characterise a range of uncertainty for future climate changes, two scenarios were selected for climate at these two points in time: ‘most wet’ (minimum warming with maximum increase of precipitation) and ‘most dry’ (maximum warming with maximum decrease of precipitation). The ‘most wet’ and ‘most dry’ scenarios, selected as a threshold where the streamflow could vary in future, are summarised in Table 3.1 (Chapter 3).
For the snow-free Basins of the Goulburn and Ovens Rivers the scenarios were applied by changing all observed daily temperatures by the scenario increment and by changing the rainfall by the scenario percentage on all days with rain. However, the applicability of such a transformation method to snow affected areas involves additional assumptions to those for snow-free areas. Long-term monthly means for minimum and mean daily temperature, as well as the precipitation involved in snow melt/accumulation modelling, must also be transformed according to the mean scenarios. This applicability is shown in the Appendix. It is based on the fact that multiplicative transformation of precipitation, combined with the multiplicative interpolation procedure for calculation of the spatially distributed daily rainfall (see Chapter 4), allows one to transform directly the equivalent precipitation obtained by the snow melt/accumulation module. Analogously, the additive nature of temperature transformation allows one to transform the historical records, interpolated and integrated over a whole catchment, directly according to the mean climate scenarios.

5.4. Climate impacts on annual and monthly flows

Changes in mean annual streamflow after application of the scenarios, listed in Table 3.1, are summarised in Table 3.2 (Chapter 3) for snow-free and in Table 5.1 for snow affected catchments. The small difference in the annual rainfall changes for different clusters of snow-free and snow-affected catchments is related to the fact that the portion of precipitation occurring in the winter period is not exactly the same for all groups of catchment. The considerable increase in annual flow for the ‘most wet’ scenarios in snow-affected areas, compared with the almost constant level of streamflow for snow-free catchments, should be emphasised.
Table 5.1. Climate impact on annual precipitation and streamflow for selected scenarios in the snow-affected catchments.

The Mitta-Mitta catchment

<table>
<thead>
<tr>
<th>Period</th>
<th>2030 precip</th>
<th>2030 flow</th>
<th>2070 precip</th>
<th>2070 flow</th>
</tr>
</thead>
<tbody>
<tr>
<td>'most dry' scenario</td>
<td>-6%</td>
<td>-32%</td>
<td>-12%</td>
<td>-59%</td>
</tr>
<tr>
<td>'most wet' scenario</td>
<td>+14%</td>
<td>+7%</td>
<td>+28%</td>
<td>+12%</td>
</tr>
</tbody>
</table>

The Kiewa catchment

<table>
<thead>
<tr>
<th>Period</th>
<th>2030 precip</th>
<th>2030 flow</th>
<th>2070 precip</th>
<th>2070 flow</th>
</tr>
</thead>
<tbody>
<tr>
<td>'most dry' scenario</td>
<td>-7%</td>
<td>-28%</td>
<td>-13%</td>
<td>-53%</td>
</tr>
<tr>
<td>'most wet' scenario</td>
<td>+13%</td>
<td>+11%</td>
<td>+27%</td>
<td>+21%</td>
</tr>
</tbody>
</table>

Figures 3.4 and 5.1 show how the 5-year running mean values for annual discharge are affected by the different climate scenarios for all groups of catchments selected and all scenarios (Tables 3.1, 3.2 and 5.1); Figures 3.4a,b,c and 5.1a,b show these results for the 5 groups of catchments listed above. The 'most wet' and 'most dry' streamflow scenarios for 2030 (dashed lines) and for 2070 (dot-dashed lines) might be considered as upper and lower thresholds for possible annual streamflow fluctuations for future climate changes.

Figure 5.2 is an example of how these scenarios affect mean monthly flows (5-year running mean values for monthly flow are presented). The case of the Ovens Basin (Figure 5.2a) is considered as an example of a snow-free region and the historical evolution of monthly discharge for February (minimum discharge) and August (maximum discharge) is presented. The March (minimum) and October (maximum) discharge of the Kiewa River (Figure 5.2b) is presented to illustrate this evolution for snow-affected areas. Figure 5.2 shows that in summer the possible relative increase in flow can be higher than in winter for both types of catchments.
Figure 5.1a. (The Kiewa River). Climate impact on annual streamflow for the 4 scenarios listed in Table 3.1. 'Most wet' and 'most dry' limits might be considered as upper and lower thresholds for possible annual streamflow fluctuations for future climate change.
Figure 5.1b. (The Mitta-Mitta River). Climate impact on annual streamflow for the 4 scenarios listed in Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered as upper and lower thresholds for possible annual streamflow fluctuations for future climate change.
Figure 5.2a. Climate impact on monthly streamflow in the Ovens Basin for 2070 scenarios from Table 3.1. ‘Most wet’ and ‘most dry’ limits might be considered as upper and lower thresholds for possible monthly streamflow fluctuations for future climate change.
Figure 5.2b. Climate impact on monthly streamflow the Kiewa Basin for 2070 scenarios from Table 3.1. 'Most wet' and 'most dry' limits might be considered as upper and lower thresholds for possible monthly streamflow fluctuations for future climate change.
The ‘most wet’ scenarios in each case lead to negligible change to the annual flow in snow-free areas. The streamflow increase in snow-affected regions is higher for the annual as well as the monthly discharge.

An analysis of possible climate impacts on monthly flows was also performed. The climate impact on mean monthly flow in the lower part of the Goulburn Basin for each month of the year (Figure 5.3a) was compared with the impact on monthly flow in the snow-affected Kiewa Basin (Figure 5.3b). The ‘most wet’ scenarios lead to negligible change during late winter-early summer (August-January) in snow-free regions and to increases in mean monthly flow during late summer-early winter (February-July). These increases at 2070 range from approximately 10% in July up to 45% for May. Increases in monthly flow were observed for every month of the year for the snow-affected Kiewa catchment. They are higher during late summer-early winter (about 20% at 2030 and 50% at 2070 for mean April flow) and lower during late winter-early summer (on average about 15% increase in flow at 2030 and 25% at 2070). A possible explanation is that the effect of warming, and therefore the increase in evaporation, cancels the effect of increasing precipitation in snow-free areas, but that the evaporation effects in the snow-affected regions are much lower.

For the ‘most dry’ scenarios in each case a very substantial reduction in streamflow was found; about 35% in 2030 and 60% in 2070 for snow-free areas and about 25% in 2030 and 50% in 2070 for snow-affected regions, on average. The lower reduction in monthly flow in snow-affected regions is also explained by lower levels of evaporation during winter in partially snow-covered catchments.

Figure 5.4 illustrates the modelled impact on mean monthly flow at 2070 for the snow-free Ovens and snow-affected Mitta-Mitta catchments for the ‘most dry’ and ‘most wet’ scenarios. This analysis shows that the annual distribution of monthly discharge does not shift
Figure 5.3a. Climate impact (in percent) on the mean monthly discharge for the snow-free catchments of the Goulburn Basin downstream of Lake Eildon.
Figure 5.3b. Climate impact (in percent) on the mean monthly discharge for the snow-affected Kiewa catchment.
Figure 5.4. Two cases of climate impact on the annual distribution of mean monthly discharge for (left column) the snow-free catchments of the Ovens River, 'most dry' and 'most wet' scenario for 2070, and (right column) the snow-affected Mitta-Mitta catchment, 'most dry' and 'most wet' scenario for 2070.
considerably under climate changes for all scenarios considered for both types of regions. August remains the month with maximum discharge for the Ovens catchment and September and October for the Mitta-Mitta catchment.

5.5. Climate impacts on extreme events: floods and droughts

The term ‘flood’ has been defined directly in terms of critical values of streamflow. The more common definition of this term as a maximum annual (biannual, decennial, etc...) discharge is less convenient for the purposes of the analysis presented below. Figure 3.7 (Chapter 3) demonstrates how the frequency of August, September and October discharge (months with the maximum mean value of streamflow discharge for the majority of the rivers under study) varies with time (for the present, 2030 and 2070) for the Upper Ovens River at Bright (gauging station 403205). If the threshold for discharge is chosen as 50 cumecs then the probability of high flow increases 41% and 81% in 2030 and 2070, respectively the (probabilities of streamflow events with discharge greater than 50 cumecs are 0.022 at present, 0.031 at 2030 and 0.040 at 2070 for ‘most wet’ scenarios, Figure 3.7b). The important fact is that the wet scenarios, providing little increase in average annual flow, gave a large increase in frequency. The probability of high flow in the ‘most dry’ scenarios sharply reduces from 0.022 at present to 0.004 at 2030 and to a zero value at 2070 (Figure 3.7a). Figure 5.5 shows the increase in probabilities, defined for the same 50 cumecs flow level, for the snow-affected Kiewa Basin. In the case of the ‘wet’ scenarios (Figure 5.5b), it is from 0.079 at present (the absolute value of discharge is more than two times higher in the Kiewa than in the Upper Ovens River), 0.096 at 2030 and 0.114 at 2070, which correspond to 22% and 44% increases, respectively. The problem of estimation of these probabilities for another
Figure 5.5a. Histograms for daily streamflow (for the period of August, September and October) for the present and the 2030 and 2070 ‘most dry’ scenarios for the snow-affected Kiewa catchment.
Figure 5.5b. Histograms for daily streamflow (for the period of August, September and October) for the present and the 2030 and 2070 'most wet' scenarios for the snow-affected Kiewa catchment.
threshold is discussed below. The probability of high flow in the ‘most dry’ scenarios reduces to the values 0.018 and 0.002 at 2030 and 2070, respectively (Fig 5.5a).

The catchment wetness index of the model, $s_k$, has been used for definition of the term ‘drought’ and for calculating changes in their frequency. Drought is defined as occurring when $s_k$ is less than 0.05. The definition of this function $s_k$ is given by the recursive relationship (Chapter 2):

$$s_k = \frac{r_k}{c} + (1 - 1/\tau_w(t_k)) s_{k-1}$$

$$\tau_w(t_k) = \tau_w \exp(20f - t_k)$$

where $r_k$ is the measured precipitation and $t_k$ is temperature. Recall also that the constant $c$ is calculated so that the volume of excess rainfall is equal to the total streamflow for the calibration period, and $\tau_w$ is a parameter reflecting the rate of drying of the catchment. The parameter $\tau_w$ and the temperature modulation factor $f$ are optimised during the model calibration. The results obtained for the Upper Ovens catchment at Bright are shown in Figure 3.8. Histograms for the frequency of the soil wetness index $s_k$ were produced using the long term streamflow simulation results. The statistical distribution of the soil wetness index at present (upper histogram), for the ‘most dry’ scenario at 2030 (middle) and the ‘most dry’ scenario at 2070 (lower) is presented in Figure 3.8a. The probability of $s_k$-events with magnitude less then 0.05 (the threshold is arbitrarily chosen as a definition of ‘drought’) increases by about 35% (from 0.17 to 0.23) for the 2030 scenario and increases by about 80% (from 0.17 to 0.31) at 2070 for the ‘most dry’ scenario. These probabilities remain much the same in the case of the ‘most wet’ scenarios (Figure 3.8b), their values are 0.17, 0.17 and 0.19 at present, at 2030 and at 2070, respectively. Similar histograms for the
Figure 5.6a. Histograms for soil wetness index for present and the 2030 and 2070 ‘most dry’ scenarios for the Kiewa River at Mongans Bridge.
Figure 5.6b. Histograms for soil wetness index for present and the 2030 and 2070 'most wet' scenarios for the Kiewa River at Mongans Bridge.
snow-affected Kiewa catchment are presented in Figure 5.6. The more uniform shape of the histograms for the Kiewa River must be emphasised. Drought probabilities for the ‘most dry’ scenarios grow from 0.144 at present to 0.196 and 0.269 at 2030 and 2070, respectively (Figure 5.6a). That corresponds to a projected 36% and 87% increase in drought probabilities in the future under our scenarios and definition of drought. These probabilities for the ‘most wet’ scenarios do not change substantially; they are 0.145 at 2030 and 0.161 at 2070 (Figure 5.6b).

5.6. Discussion and conclusions

The conceptual rainfall-runoff model IHACRES was calibrated and validated, and its performance documented, for four Basins in eastern Victoria in Chapters 2 and 4. The model provides good performance in snow-free areas (the Goulburn and Ovens Basins) as well as in snow-affected catchments (the Kiewa Basin and the Mitta-Mitta catchment in the Upper Murray Basin), where the snow melt/accumulation module based on a modified degree-day approach was applied. The total discharge of the rivers modelled constitutes more than 4,000,000 ML per year and their total drainage area is about 8,750 km². The reliability of the selected model allowed its use for estimation of the possible climatic impacts on the streamflow, albeit under the assumption that overall vegetation conditions in the region under study remain similar in their basic evapotranspiration response to changes in temperature.

Two important limitations of the model’s applicability to the estimation of possible climate impacts in the snow-affected areas must be noted. Firstly, the methodology assumes that the parameters of the IHACRES model, as well as those of the snow melt/accumulation module remain constant under different climatic conditions and are only a function of the catchment landscape characteristics and vegetation cover. The temperature modulation factor ($f$) in the non-linear part of the IHACRES model and the degree-day factor in the snow
melt/accumulation module may be seriously affected by possible climate change. The latter is a complicated integral parameterisation for many processes such as radiation, heat flux, internal snowpack processes etc. A comprehensive analysis of how the processes of snow formation and melt might be affected by climate changes can be found in Oglesby (1990).

The second limitation is related to the assumption presuming that fluctuations in the evaporation rate with time depends only on temperature. This is a more acceptable assumption for snow-free areas where evaporation from the surface is higher than that covered by snow under equivalent temperature conditions. This simplification is unacceptable for catchments where a major part of the surface is covered by snow in winter. However, this assumption seems reasonable for the catchments in the region considered because only 10% to 20% of their areas are covered by snow in winter.

Climate scenarios developed for the Australian region were employed for estimating the possible climate impacts on water availability in these Basins. Two extreme cases were considered: a ‘most dry’ scenario yielding a minimum amount of river runoff and a ‘most wet’ scenario yielding a maximum amount. These two cases might define the lower and upper limits respectively for total discharge of the rivers in the region considered under the enhanced greenhouse effect. However, as well as changes in the mean climate in the future, there may be changes in other temperatures of the distribution. Changes in frequency at either the upper or lower end of precipitation especially will affect extreme streamflow predictions most. Hopefully, the wide band between our ‘most wet’ and ‘most dry’ scenarios provides an indication of how serious climate impacts on streamflow might be in the future. As information on the distributional changes in precipitation and temperature becomes available this can be used to update the climatic inputs to our calibrated models for these Basins.
For two dates in the future, 2030 and 2070, the reduction in annual discharge reaches 28% - 38% for 2030 and 53% - 64% for 2070; the amount of water decreases more in snow-free catchments than this in snow-affected regions, although the difference between these two types of catchments is small. The ‘most wet’ scenarios provide slightly different impacts for snow-free and snow-affected catchments: it is negligibly small (between 3% reduction and 4% increase at 2030 and 0% - +6% at 2070) for snow-free areas, whereas it is considerably higher for snowy Basins (11% increase for the Kiewa catchment and 7% increase for Mitta-Mitta at 2030, 21% and 12% increase for these catchments at 2070, respectively). As these values for snow-free areas are very close to the predictive error in the model, the current streamflow discharge regime could be considered similar to the conditions provided by the ‘most wet’ scenarios. In this case evaporation resulting from increased warming cancels the maximum possible increase in rainfall.

The analysis of climate impacts on mean monthly flow shows that the higher increase in mean annual streamflow under the ‘most wet’ scenarios in snow-affected regions can not be explained by the redistribution of the monthly discharge by snow melt excesses or snow formation losses. A possible explanation is that the effect of warming and, therefore, the increase in evaporation, cancels the effect of increasing precipitation in snow-free areas, but that the evaporation effects in the snow-affected regions are much lower. As a considerable increase in precipitation is the main characteristic of the ‘most wet’ scenario, a more significant effect is that the relative losses decrease faster with increases in precipitation in the snow-affected than in snow-free regions. The result can be illustrated empirically, using long-term streamflow observations for both types of catchments. Figure 5.7 illustrates the distribution of annual proportional losses, calculated as \((1 - \text{annual runoff/annual precipitation}) \times 100\%\), against annual precipitation for the Ovens River (snow-free) and the Kiewa River (snow-affected) catchments. Data over a 40-year period were used for the
Ovens River at Bright while a 20-year series was used for the Kiewa River. The regression lines shown in Figure 5.7 illustrate that proportional losses reduce faster as precipitation increases for the snow-affected area (slope of regression line is -0.021, with standard deviation 0.004) than for those in the snow-free catchment (slope of regression line is -0.01, with standard deviation value 0.004).

Flood frequency, defined for this study as a streamflow event with daily discharge higher than 50 cumecs, was found to increase for the ‘most wet’ scenarios; to 41% at 2030 and 81% at 2070. The important fact is that a small increase in the absolute value of flow provides considerable increase in the probability of high flow. The probability of high flow for the ‘most dry’ scenarios rapidly decreases from 0.022 at present to 0.004 at 2030 and to a zero value at 2070 for snow-free catchments. The increase of probabilities for the snow-affected Kiewa Basin (also defined as a 50 cumecs threshold) in the case of the ‘most wet’ scenarios is from to 0.079 at present, 0.096 at 2030 and 0.114 at 2070, which correspond to 22% and 44% growth, respectively. As the absolute value of discharge is more than two times higher in the Kiewa than in the Upper Ovens River, another threshold may be chosen for definition of ‘floods’ in the Kiewa Basin. If the ‘floods’ are defined as streamflow events with discharge higher than 65 cumecs (the probability of such events, 0.024, at present is almost the same as the probability of streamflow events with discharge greater than 50 cumecs for the Upper Ovens). These probabilities increase to 0.039 and 0.053 at 2030 and 2070, respectively, corresponding to 62% and 120% relative increases at these dates. The general conclusion is that the high flow probabilities are slightly higher for snow-affected catchments. However their projected growth in the future under our assumptions can be summarised as about 50% at 2030 and 100% at 2070 for both types of catchments. The probability of high flow events for the ‘most dry’ scenarios for the Kiewa catchment reduces to the values 0.018 and 0.002 at 2030 and 2070, respectively.
Figure 5.7. Proportional annual losses for the snow-free Ovens River catchment (above) and the snow-affected Kiewa River catchment (below). The regression lines of proportional losses against annual precipitation are indicated.
Drought frequency, as defined by the soil wetness index, increased 35% for the ‘most dry’ scenario at 2030 and 80% for the ‘most dry’ scenario at 2070 for snow-free areas and, similarly, 36% and 87% for the snow-affected Kiewa River. The similarity of results received for snow-free and snow-affected regions naturally corresponds to the fact that, even in the alpine areas, snow processes are negligibly small during the summer period.

The results above are similar to those obtained by Whetton *et al.* (1993) but are more optimistic regarding droughts.

The models, selected for each of the catchments, were used for estimating future climate impact under the assumption that the overall vegetation response to a given precipitation and temperature regime in the area considered will remain constant. Considerable changes in land use or deforestation in this area in future may provide more dramatic changes in the discharge response of these Basins. The effects on transpiration of elevated levels of carbon dioxide are also not quantitatively known. A second limitation of the approach suggested is related to the high level of uncertainty in the estimated mean climatic patterns, mirrored in the large differences in streamflow values associated with the selected scenarios. A third multivariate distributional properties and temperature (which presently only mean is the presently unknown values of climate variables such as precipitation to be stipulated in scenarios). Application of climatic time series properties obtained by Global Climate Models with high spatial resolution or by Limited Area Models, developed for the region considered, combined with the use of weather simulation models designed to presence a desired structure in the multivariate distribution of climate variables, is one way to gain more accurate estimation of streamflow events in future.
5.A Appendix

How to scale climatic data in snow-affected catchments?

In contrast to snow-free Basins, calibrated largely on the basis of single station meteorological records, the snow-affected catchments have been calibrated using climate data interpolated over the whole area under consideration taking into account information from all available meteorological stations. The procedure for spatial interpolation of daily climate records using the long term monthly means, described in Section 4.3, is as follows:

Precipitation was computed using an assumption that the ratio of long-term mean monthly rainfall, taken for each gridcell, to the mean monthly rainfall, calculated for the nearest gauging station (base station) is equal to the ratio of rainfall of each particular day for this gridcell to rainfall measured at this day at the same station:

\[
r_k^{\text{int}}(i,j) = r_k^{\text{station}} \cdot \frac{r_l^{\text{mean}}(i,j)}{r_l^{\text{mean}}(\text{station})},
\]

(5.A.1)

where \( k \) indicates day number, \( r_k^{\text{int}}(i,j) \) is interpolated daily rainfall for the gridcell with coordinates \((i,j)\), \( r_k^{\text{station}} \) is rainfall measured at the station on day \( k \), \( r_l^{\text{mean}}(i,j) \) is the long term mean rainfall for the month \( l \) \((l=1,2,...,12)\) calculated for this gridcell and \( r_l^{\text{mean}}(\text{station}) \) is the long term mean calculated for the site of the station location.

The interpolated daily temperature for each gridcell was calculated using the following assumption: that the difference between the daily temperature in each gridcell and the long term monthly mean value of the temperature taken in this gridcell for a particular month is equal to the difference between the daily temperature measured at the nearest station at this day and the long term mean value of the temperature calculated for the gridcell where the station is located for this month:
\[ t^\text{int}(i,j) - t^\text{mean}(i,j) = t^\text{d}(\text{station}) - t^\text{mean}(\text{station}), \]  

(5.A.2)

where \( k \) is day number, \( t^\text{int}(i,j) \) is interpolated daily temperature for the gridcell with coordinates \((i,j)\), \( t^\text{mean}(i,j) \) is the long term mean temperature for the month \( l \) estimated for this gridcell, \( t^d(\text{station}) \) is temperature measured at the station on day \( k \) and \( t^\text{mean}(\text{station}) \) indicates the long term mean temperature calculated for the station site. This interpolation procedure was applied to daily mean as well as to daily minimum temperatures.

It is possible to calibrate separately all long term mean monthly statistics and daily records from the base stations according to given scenarios (procedure 1) or to scale integrated values of equivalent rainfall and integrated temperature (procedure 2). If the additive calibration correction \( T \) for the temperature and multiplicative one \( P \) for precipitation is applied to the daily measured values \( t^d(\text{station}) \) and \( r^d(\text{station}) \) as well as to the long term monthly means \( t^\text{mean}(i,j), t^\text{mean}(\text{station}), r^\text{mean}(i,j) \) and \( r^\text{mean}(\text{station}) \), then it follows from the formulae (5.A.1) and (5.A.2), that these two procedures are equivalent.
CHAPTER 6

A DETERMINISTIC-STOCHASTIC STREAMFLOW FORECASTING ALGORITHM AND ITS APPLICATION TO THE UPPER MURRAY BASIN.

Summary

This Chapter describes the results of runoff modelling of catchments of the Upper Murray Basin of the Murray Darling Drainage Division (MDDD). One aim was to provide adequate models for streamflow prediction in nine gauge catchments of this Basin feeding the Hume and Dartmouth reservoirs. Another was the development and testing of flow forecasting algorithms for operational management by the Murray-Darling Basin Commission. This Chapter outlines the modelling work accomplished for all nine selected catchments on a daily time step, and for Tallangatta Creek on a 4-hourly time step.

The conceptual lumped parameter rainfall-runoff model IHACRES (Chapter 2) was selected as the modelling tool for streamflow prediction in the catchments. For snow-affected catchments, the snow melt/formation module (Chapter 4) was applied. The IHACRES model is referred to later as the 'deterministic component' of the streamflow forecasting algorithm.

The conceptual rainfall-runoff model IHACRES (with a snow melt/formation module in snow-affected catchments) and a self-adaptive linear filtering approach were combined and applied for forecasting daily streamflow for nine catchments in the Upper Murray Basin.
Different types of models were considered in order to select the most appropriate forecasting algorithm. The additional operation of linear filtering of the conceptual model residuals provides considerable improvement in forecasting for both low and high values of streamflow. The AutoRegressive Integrated Moving Average (ARIMA) modelling of the residuals was selected for the linear filtering, and tested for performance as part of an operational streamflow forecast system. The ARIMA module is referred to later as the 'stochastic component' of the streamflow forecasting algorithm.

6.1. Introduction

6.1.1. Background

Overton and Meadows (1976) define three basic categories for streamflow forecasting methods based upon: (1) regression-type analysis, (2) time series analysis and (3) flow frequency analysis. The regression-type analysis uses an optimisation procedure where a causal model is structured as a linear or slightly non-linear approximation. Least squares (or modified least squares) regression serves as a tool for this approximation of modelled values against empirical data. Although not strictly a regression model, the IHACRES model can be classified as belonging to this type of method. Time series analysis, applied in the present Chapter for operational streamflow forecasting, "analyses a continuous time series of runoff and draws an inference as to the underlying generating mechanism" (Overton and Meadows, 1976). Frequency analysis is entirely probabilistic, and is usually used for catchments where streamflow data are continuously recorded but no rainfall records are available. Primarily it is applied in order to evaluate the probabilities of extreme flow values, both high and low. A comprehensive review of the literature on applications of time series analysis techniques in hydrology is out of the scope of the present work but several publications should be
mentioned here. Two classical monographs specially devoted to the problem of time series analysis are Box and Jenkins, (1976) and Bras and Rodriguez-Iturbe (1985), where a detailed description of the ARIMA algorithm used in this work can be found. The term self-adapting approach, is used here when the parameters values are updated to be optimal in some sense for the current time interval. The use of self-adapting models involving residual updating as used here applied to flash flood forecasting are described in a range of publications (Wood, 1989; Georgakakos, 1987). An approach combining a deterministic seven parameter model SM2 with ARIMA modelling was applied by Jamieson et al. (1972). The residual variance of the composite model was significantly less than that attainable by using the deterministic model only. A similar methodology to that here was suggested by Brath and Rosso (1993). The main difference between their approach and the method applied here is that in our approach calibration of the conceptual model is made once on a 2 year period, then its parameters are considered unchanging for the period of observation. The linear filtering algorithm is than applied to the model residuals. In Brath and Rosso (1993) the stochastic algorithm was applied solely and directly to streamflow time series.

Whereas ARIMA modelling considers the streamflow time series solely in order to provide the optimal forecast, some linear filtering algorithms analyse the time series of the precipitation and streamflow together. The filtering of input precipitation data using an ARMAX modification of the ARIMA method is described, for example, in Karlsson and Yakowitz (1987). The ARMAX (X means the use of $eXogenous$ variables, precipitation for instance) algorithm is a compromise between prediction techniques based on a deterministic relation of streamflow with rainfall input (affected by errors of measurement), and ARIMA models applied solely, where no information on precipitation is used.
More sophisticated techniques for streamflow forecasting are based on Kalman filtering (Kalman, 1960). An example of the application of this technique can be found in Sen (1991), where orthogonal Walsh series, used for describing the periodic component, was combined with the Kalman filter. This method was applied to the prediction of monthly flow for two catchments in Turkey and the United States and for monthly rainfall prediction in Saudi Arabia. The Kalman filter technique is used in the European Flood Forecasting Operational Real-Time System (EFFORTS), widely applied to water resource management in Europe and worldwide (Todini, 1996). This method is based on two linear, interactive Kalman filters, one in the space of the state vector and another in the space of the parameters (which relate streamflow to precipitation).

Another new technique widely used for streamflow forecasting is the Nearest Neighbouring Method (NNM). The NNM, closely related to techniques of non-linear dynamics, has been developing quickly over the last decade (Olason and Watt, 1986; Mack and Rosenblatt, 1979; Yakowitz, 1987; Yakowitz and Karlsson, 1987; Galeati, 1990). This method is based on the assumption that the streamflow time series is an output of a deterministic dynamic system with stochastic noise. Kember and Flower (1993) reported that the NNM provides improvement in forecasting compared with the ARIMA model. It main advantage is that it does not require the stochastic noise to possess an assumed structure.

Streamflow routing models are often a part of operational streamflow forecasting systems. They allow incorporation of the streamflow from remotely located gauging sites into prediction of flow downstream; for instance, inflows to reservoirs. A capable flow routing algorithm is useful for different hydrological applications, especially as a part of an integral scheme of operational reservoir management (Georgakakos and Marks, 1987; Georgakakos, 1989). Chow (1964) classifies flow routing algorithms into two broad types: reservoir routing
and open-channel routing. The first type involves methods for describing the effects on a flood wave passing through a reservoir. Open-channel algorithms are applied for estimating the timing and magnitude of flood waves in rivers. A general description and classification of pioneering work on flow routing can be found in Chow (1964). However, in more recent publications classical results on flow routing are used. Georgakakos et al. (1990) proposed a state space formulation of the Muskingam routing scheme (Nash, 1959; Carter and Godfrey, 1960; Overton, 1966). This formulation uses real-time streamflow measurements, model values and errors. The technique allows real-time updating of the forecasted flow through the Kalman filter estimator. Formulation of a methodology where a deterministic routing scheme with constant coefficients is updated by a stochastic module is described, for instance, in Hoos et al. (1989). This method was tested on two sites with different geomorphological conditions. An example of modern routing techniques is used in the RORB model, widely employed for estimating of magnitude of extreme flow events in Australia (Dayer, 1994a,b). The advantage of this model is its applicability to ungauged catchments, because its parameters might be established using the geomorphological properties of the area where streamflow needs to be modelled.

In conclusion it should be stated explicity that the ARIMA algorithm was chosen here among other filtering methods because, for a modest investment, it offered the potential to provide an effective combination with deterministic predictions of streamflow (using the IHACRES model here) for forecasting. While this proved to be the case, some of the more advanced and complicated algorithms mentioned above will be tested in the future for streamflow forecasting in the region considered.
6.1.2. The Upper Murray Basin description

The Upper Murray Basin is located in the south-eastern part of the MDDD and covers 15,300 km$^2$ of territory in the states of Victoria (the Mitta-Mitta River catchment and the left bank of the Murray River with a total area of 1,000 km$^2$) and New South Wales (Figure 6.1). River flows are regulated by Hume and Dartmouth reservoirs operated by the Murray-Darling Basin Commission (MDBC). The River Murray Water Agreement regulates redistribution of water in this Basin between the states of Victoria and New South Wales. The climate characteristics of the Basin and the physiography of its Victorian part were described in Section 4.2. The right bank of the Murray catchment belongs to the New South Wales part of the Basin. The largest water contributors in this area are the right side of the Upper Murray River at Biggara (1,165 km$^2$) and the Tooma River catchment at Pine Grove (1,819 km$^2$). These two catchments gain water from the western slopes of the Snowy Mountains which is the highest region in Australia (Mt Kosciusko 2228 m a.s.l). The outlet of an inter-basin water transfer, via the Snowy Mountains Hydroelectric Scheme, providing 580,000 ML annually on average, is located in this part of the Basin. The Jingellic Creek catchment is located in the north of the New South Wales part of the Basin.

About 80% of the area of the Upper Murray Basin is forested, although all the major valleys which lie in its north have been cleared for agriculture (Water Victoria, 1989). Water use in this Basin is small (4,830 ML per year on average). However, it is one of the major contributors of water resources to the MDDD, especially to its Victorian part.

Streamflow information for the nine catchments selected for analysis here is used by the MDBC for calculating inlet flows to the Hume and Dartmouth reservoirs. The mean annual discharge and areas of these catchments are presented in Table 6.1.
Figure 6.1. River network, meteorological and discharge stations for the catchments under consideration in the Upper Murray Basin.
Table 6.1. The catchments of the Upper Murray Basin selected for modelling/forecasting.

<table>
<thead>
<tr>
<th>Station number</th>
<th>River and station location</th>
<th>Mean annual discharge (ML)</th>
<th>Area (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>401203</td>
<td>Mitta-Mitta River at Hinnomunjie</td>
<td>475,000</td>
<td>1533</td>
</tr>
<tr>
<td>401220</td>
<td>Tallangatta Creek at McCallums</td>
<td>71,900</td>
<td>464</td>
</tr>
<tr>
<td>401208</td>
<td>Cudgewa Creek at Berringama</td>
<td>102,000</td>
<td>350</td>
</tr>
<tr>
<td>401012</td>
<td>Murray River at Biggara</td>
<td>532,000</td>
<td>1165</td>
</tr>
<tr>
<td>401217</td>
<td>Gibbo River at Gibbo</td>
<td>135,000</td>
<td>389</td>
</tr>
<tr>
<td>401210</td>
<td>Snowy Creek at Granite Flat</td>
<td>195,000</td>
<td>407</td>
</tr>
<tr>
<td>401013</td>
<td>Jingellic Creek at Jingellic</td>
<td>66,000</td>
<td>328</td>
</tr>
<tr>
<td>401014</td>
<td>Tooma River at Pine Grove</td>
<td>442,000</td>
<td>1819</td>
</tr>
<tr>
<td>401216</td>
<td>Big River U/S of Joker Ck</td>
<td>231,000</td>
<td>356</td>
</tr>
</tbody>
</table>

6.2. Results of runoff modelling (snow-free catchments)

6.2.1. The Tallangatta and Cudgewa Creek catchments

The Tallangatta and Cudgewa Creek catchments were considered as snow-free to a first approximation. They were modelled using, as an input, meteorological records from single stations. Tallangatta Creek was modelled using streamflow data from McCallums gauging station (401220) for the period 1976-90 and the Bullioh station (401218) for the period 1954-75; precipitation data were from the meteorological station at Tallangatta (82047). Streamflow data for Cudgewa Creek were taken from the station at Berringama (401208).
and precipitation from the station at Corryong (82011). The temperature data for both catchments were taken from the Corryong station. These two catchments were calibrated on 10 almost non-overlapping calibration periods (CPs) each of two years. Successful calibrations, for example with efficiency $E > 0.750$, were obtained for five CPs for Tallangatta Creek and three CP's for Cudgewa Creek (see Table 6.2). The model efficiency statistics for the best calibration periods were 0.903 for Tallangatta Creek and 0.872 for Cudgewa Creek.

The calibration results obtained for these catchments on CP 5 (Table 6.2) are shown in Figures 6.2 and 6.3. Long-term simulation of daily streamflow implemented for Tallangatta and Cudgewa Creeks over 1972-1990 provide efficiency and bias statistics of (0.611; 0.35) and (0.638; 062), respectively, for the models selected as best (these are the models calibrated on CP 5 for both catchments). In such simulation (see Section 2.5.1), the values of the parameters $\tau_w, f, c$, and the coefficients in the linear module of the IHACRES model, optimised during the calibration runs, were used for modelling daily streamflow using the rainfall and temperature series as model inputs for the whole period where precipitation, temperature and streamflow data are available.

6.2.2. The Jingellic Creek catchment

The Jingellic Creek catchment was considered as snow-free to a first approximation. It was modelled using, as an input, precipitation records from the single meteorological station at Koetong N 82024. The streamflow data were taken from station N 401013 at Jingellic. The temperature data were taken from the Corryong station. This catchment was calibrated on 8 almost non-overlapping calibration periods each of two years. Calibrations, with efficiency coefficient $E > 0.700$, were obtained for three CP’s (see Table 6.3). The calibration results obtained on CP 8 are shown in Figure 6.4. The poor performance of the model on the other CP’s is related to defects in streamflow records of gauging station N 401013. Jingellic Creek is an
ephemeral river that is more difficult to model than the other catchments. This partly explains why long-term simulation (using the best model calibrated on CP 8) provides relatively poor results here \((E = 0.533)\). The selected structure of the IHACRES model used here cannot approximate streamflow when it reaches a zero level. However, such periods are relatively short for this catchment and its calibration using the version of the model oriented to ephemeral rivers (see Section 2.5.4 of Chapter 2) does not seem justified.

Table 6.2. Model efficiency values \(E\) for calibration of the IHACRES model for the Tallangatta and Cudgewa Creeks catchments.

<table>
<thead>
<tr>
<th>Catchment and station number</th>
<th>The Tallangatta Creek 401220</th>
<th>The Cudgewa Creek 401208</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 25/02/72-24/02/74</td>
<td>0.789</td>
<td>-</td>
</tr>
<tr>
<td>2 24/02/74-23/02/76</td>
<td>0.837</td>
<td>-</td>
</tr>
<tr>
<td>3 4/03/76-3/03/78</td>
<td>-</td>
<td>0.768</td>
</tr>
<tr>
<td>5 10/12/79-9/12/81</td>
<td>0.903</td>
<td>0.872</td>
</tr>
<tr>
<td>6 9/12/81-8/12/83</td>
<td>0.858</td>
<td>-</td>
</tr>
<tr>
<td>8 28/12/85-17/12/87</td>
<td>0.809</td>
<td>0.840</td>
</tr>
</tbody>
</table>

- denotes model performance \((E < 0.700)\).

Table 6.3. Model efficiency values \(E\) for calibration of the rainfall-runoff model for the Jingellic Creek catchment.

<table>
<thead>
<tr>
<th>CP</th>
<th>Model efficiency (E)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 20/12/79-19/12/81</td>
<td>0.709</td>
</tr>
<tr>
<td>7 19/12/83-18/12/85</td>
<td>0.703</td>
</tr>
<tr>
<td>8 28/12/85-26/12/87</td>
<td>0.797</td>
</tr>
</tbody>
</table>
Figure 6.2. Observed (solid line), modelled (dashed line) streamflow (cumecs) for CP 5 (1980-1981) for the Tallangatta Creek catchment.
Figure 6.3. Observed (solid line), modelled (dashed line) streamflow (cumecs) for the CP 5 (1980-1981) for the Cudgewa Creek catchment.
Figure 6.4. Observed (solid line), modelled (dashed line) streamflow (cumecs) for CP 8 (1986-1987) for the Jingellic Creek catchment.
6.3. Results of runoff modelling (snow-affected catchments)

6.3.1. *The Mitta-Mitta River catchment*

Model calibration for the snow-affected Mitta-Mitta catchment was described in Chapter 4. Successful calibrations were obtained and the calibration results, in terms of model efficiency, are summarised in Table 4.2. Simulation results are summarised in Table 4.3. Figure 4.10b shows the model fit to the measured daily flow for the Mitta-Mitta River on CP 8 (see Table 4.2). The results described above show that the IHACRES model, applied to the snow-affected catchments and combined with the snow melt/accumulation module, provides a fit of the model to the observed data of about the same quality as this model (without the module) achieves when it is applied in snow-free basins; cf. Chapter 2 where the results of the IHACRES application to the practically snow-free Goulburn and Ovens Basins are described.

6.3.2. *The Upper Murray at Biggara, Gibbo River and Snowy Creek catchments*

Model calibration for the snow-affected catchments of the Upper Murray at Biggara, Gibbo River and Snowy Creek was performed with daily time series of the following:

1. equivalent precipitation, estimated by the snow melt/accumulation module (Nariel Creek meteorological station N 82035 was selected as the base for the Upper Murray catchment, Gibbo River Park station N 82018 for the Gibbo River and Mitta-Mitta Forestry station N 82068 for Snowy Creek).

2. temperature, interpolated for each grid cell of the catchment and then integrated over this catchment (Corryong meteorological station 82011 was selected as the base for the whole region under consideration), and

The period 1973-1987 was divided into 7 CPs, each with a duration of two years. The selected CP's do not overlap substantially, with the one exception of CP 7 for the Gibbo River because of lack of streamflow data after 30 June 1986. Successful calibrations were obtained and the calibration results, in terms of model efficiency, are summarised in Table 6.4. Figures 6.5-6.7 show the model fit to the measured daily flow for these three catchments for CP 7 (the Upper Murray), CP 4 (the Gibbo River) and CP 7 (Snowy Creek).

Table 6.4. Model efficiency values $E$ for calibration of snow runoff for the Upper Murray, Gibbo Rivers and Snowy Creek catchments.

<table>
<thead>
<tr>
<th>Catchment and station number CP</th>
<th>The Upper Murray River 401012</th>
<th>The Gibbo River 401217</th>
<th>Snowy Creek 401210</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 01/01/73-31/12/74</td>
<td>-</td>
<td>0.799</td>
<td>0.741</td>
</tr>
<tr>
<td>2 01/01/75-31/12/76</td>
<td>-</td>
<td>0.710</td>
<td>-</td>
</tr>
<tr>
<td>3 06/01/77-06/01/79</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>4 20/11/78-19/11/80</td>
<td>0.810</td>
<td>0.850</td>
<td>0.792</td>
</tr>
<tr>
<td>5 01/01/81-22/12/82</td>
<td>0.852</td>
<td>0.892</td>
<td>0.792</td>
</tr>
<tr>
<td>6 13/01/83-12/01/85</td>
<td>-</td>
<td>0.801</td>
<td>-</td>
</tr>
<tr>
<td>7* 13/01/85-13/01/87</td>
<td>0.792</td>
<td>0.773</td>
<td>0.856</td>
</tr>
</tbody>
</table>

- denotes model's poor performance ($E < 0.700$).

*19/10/84-30/06/86 for the Gibbo River.

In order to check the consistency of the results obtained, simulation runs were performed over the 10-year period 1977-1987 with all of the calibrated models for each catchment. The efficiency coefficients $E$ and mean daily bias for these simulation tests are shown in Table 6.5, for the models selected as best (Section 2.6). Figure 6.8 shows the simulation performance of
Figure 6.5. Observed (solid line), modelled (dashed line) streamflow (cumeCS) for CP 7 (1985-1986) for the Upper Murray River catchment.
Figure 6.6. Observed (solid line), modelled (dashed line) streamflow (cumecs) for the CP 4 (1979-1980) for the Gibbo River catchment.
Figure 6.7. Observed (solid line), modelled (dashed line) streamflow (cumecs) for the CP 7 (1985-1986) for the Snowy Creek catchment.
Figure 6.8. Observed (solid line), modelled (dashed line) streamflow (cumeecs) for simulation results over the period 1978-1980 for the Snowy Creek catchment.
the model calibrated on CP 7 (1984-1986) over the period 1979-1980 for the Snowy Creek catchment.

Table 6.5 Simulation results over the 10 year period from 01/01/1977.

<table>
<thead>
<tr>
<th>Catchment</th>
<th>Number of CP where the model was calibrated (Table 6.4)</th>
<th>Efficiency ( E )</th>
<th>Bias (mean daily absolute error) cumecs/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>Murray River at Biggara</td>
<td>7</td>
<td>0.649</td>
<td>0.37</td>
</tr>
<tr>
<td>Gibbo River at Gibbo</td>
<td>4</td>
<td>0.692</td>
<td>0.63</td>
</tr>
<tr>
<td>Snowy Creek at Granite Flat</td>
<td>5</td>
<td>0.729</td>
<td>0.06</td>
</tr>
</tbody>
</table>

6.3.3. The Tooma and Big River catchments

Model calibration for the snow-affected catchments of Tooma River at Pine Grove and Big River upstream of Joker Creek was performed with daily time series of the following:

1. equivalent precipitation, estimated by the snow melt/accumulation module (Towong Upper meteorological station N 82060 was selected as the base for the Tooma River and Mt Beauty station N 83023 for the Big River).

2. temperature, interpolated for each grid cell of the catchment and then integrated over this catchment (The Corryong meteorological station N 82011 was selected as the base for the Tooma River catchment and Mt Beauty station N 83023 for the Big River), and

For the Tooma River the period 1973-1987 was divided into 7 CPs, each with a duration of two years. The selected CP's do not overlap substantially. Successful calibrations were obtained for 5 of 7 CP's and the calibration results, in terms of model efficiency, are summarised in Table 6.6. Figure 6.9 shows the model fit to the measured daily flow for this catchment for CP 7 (19/10/1984-30/06/1986).

Table 6.6. Model efficiency values $E$ for calibration of snow runoff for Tooma River.

<table>
<thead>
<tr>
<th>Catchment and station number CP</th>
<th>Model efficiency $E$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 01/01/73-31/12/74</td>
<td>0.703</td>
</tr>
<tr>
<td>2 01/01/75-31/12/76</td>
<td>0.782</td>
</tr>
<tr>
<td>3 06/01/77-06/01/79</td>
<td>-</td>
</tr>
<tr>
<td>4 20/11/78-19/11/80</td>
<td>0.702</td>
</tr>
<tr>
<td>5 01/01/81-22/12/82</td>
<td>0.803</td>
</tr>
<tr>
<td>6 13/01/83-12/01/85</td>
<td>-</td>
</tr>
<tr>
<td>7 13/01/85-13/01/87</td>
<td>0.773</td>
</tr>
</tbody>
</table>

- denotes model poor performance ($E < 0.700$).

The Big River is a tributary of the Mitta-Mitta catchment. Its watershed is located in the north-western part of the Mitta-Mitta catchment. The period 1965-1985, when the meteorological data were available, was subdivided into 9 non-overlapping calibration periods each of two years, the same as for the Mitta-Mitta River. Successful calibrations were
Figure 6.9. Observed (solid line), modelled (dashed line) streamflow (cumeecs) for CP 7 (1985-1986) for the Tooma River catchment.
Figure 6.10. Observed (solid line), modelled (dashed line) streamflow (curnecs) for CP 1 (1966-1967) for the Big River catchment.
obtained for 6 of the 9 CP’s and the calibration results are summarised in Table 6.7. Figure 6.10 shows the calibration results for this catchment obtained for CP 1 (4/02/1966-3/02/1968).

Table 6.7. Model efficiency values $E$ for calibration of snow runoff for the Big River.

<table>
<thead>
<tr>
<th>Catchment and station number</th>
<th>Model efficiency $E$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 4/02/66-3/02/68</td>
<td>0.862</td>
</tr>
<tr>
<td>2 5/01/68-4/01/70</td>
<td>-</td>
</tr>
<tr>
<td>3 23/02/70-22/02/72</td>
<td>-</td>
</tr>
<tr>
<td>4 24/03/72-23/03/74</td>
<td>-</td>
</tr>
<tr>
<td>5 14/03/74-13/03/76</td>
<td>0.770</td>
</tr>
<tr>
<td>6 2/02/76-1/02/78</td>
<td>0.836</td>
</tr>
<tr>
<td>7 2/02/78-1/02/80</td>
<td>0.734</td>
</tr>
<tr>
<td>8 11/02/80-10/02/82</td>
<td>0.792</td>
</tr>
<tr>
<td>9 10/02/82-9/02/84</td>
<td>0.894</td>
</tr>
</tbody>
</table>

-denotes model poor performance ($E \leq 0.700$).

In order to check the accuracy of the models over long periods, simulation runs were performed. For the Tooma River it was accomplished over the 14-year period 1973-1987 for each of 5 models with calibration efficiency greater than 0.700. For two models, calibrated on CP’s 2 and 4, the simulation results provided an efficiency higher than 0.650. These efficiency coefficients $E$ and the mean daily bias for the simulation runs are shown in Table 6.8. A simulation run for the Big River was performed over the 20 year period, 1965-1984, for every model obtained. The efficiency coefficients and bias for that catchment are shown in Table 6.9. The simulation results on the 2-year period, 1966-1967, for the model calibrated on CP 5 (14/03/1974-13/03/1976), are presented in Figure 6.11.
Figure 6.11. Observed (solid line), modelled (dashed line) streamflow (cumeecs) for simulation results over the period 1966-1967 for the Big River catchment.
Table 6.8. Simulation results over the 14-year period from 01/01/1973 for the Tooma River. Bold values denote the best selected model.

<table>
<thead>
<tr>
<th>Number of calibration period (Table 6.6)</th>
<th>Efficiency $E$</th>
<th>Bias (mean daily absolute error) cumecs/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.664</td>
<td>0.98</td>
</tr>
<tr>
<td>4</td>
<td>0.663</td>
<td>3.25</td>
</tr>
</tbody>
</table>

Table 6.9. Simulation results over the 20-year period from 01/01/1965 for the Big River. Bold values denote the best selected model.

<table>
<thead>
<tr>
<th>Number of calibration period (Table 6.7)</th>
<th>Efficiency $E$</th>
<th>Bias (mean daily absolute error) cumecs/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.693</td>
<td>0.76</td>
</tr>
<tr>
<td>5</td>
<td>0.709</td>
<td>-0.18</td>
</tr>
<tr>
<td>6</td>
<td>0.648</td>
<td>-1.10</td>
</tr>
<tr>
<td>7</td>
<td>0.646</td>
<td>0.47</td>
</tr>
<tr>
<td>8</td>
<td>0.657</td>
<td>1.81</td>
</tr>
<tr>
<td>9</td>
<td>0.656</td>
<td>0.27</td>
</tr>
</tbody>
</table>

The results of a long-term historical simulation for Tallangatta and Cudgewa Creek catchments are shown in Figure 6.12. This figure illustrates that the simulation results are reasonably good for almost all periods except for large flows in 1956 and 1974. The huge underestimations which occurred in these years might be explained by instrumental errors related to periods of very high streamflow (for instance, the poor calibration of the upper part of river profile sections for relevant stream gauging stations). Certainly the volume of ‘observed’ flow is much larger in these years than the estimated areal volume of precipitation.
Figure 6.12. Historical simulation of annual streamflow for the Tallangatta and Cudgewa Creeks using the IHACRES model.
6.4. Modelling on a 4-hourly time step

Calibration on a 4-hourly timestep was performed for the snow-free catchment of Tallangatta Creek, where such data are available for the McCallums station (N 401230). The 4-hourly precipitation data needed for calibration were taken from Granite Flat station. This station is located about 25 km to the south of the stream gauging station (same location as streamgauging station N 401210 in Figure 6.1). The 4-hourly temperature data were also interpolated from the minimum and maximum daily temperature records of Corryong meteorological station (N 82011) using the sine-logarithmic algorithm developed by Linvill (1990). It is based on the assumption of a sinusoidal approximation to temperature during the day time with a maximum at 2 hours after the solar noon and a logarithmic decrease of temperature from sunset to the minimum at sunrise. The 4-hourly streamflow data were available for the period 1/01/1991-8/02/1995. The rainfall data were recorded for the same period. However, only two relatively long periods of continuous recording exist: 3/01/1991-4/09/1991 and 2/06/1993-14/05/1994. This lack of observations does not allow calibration of the model outside these time intervals.

The models were calibrated in two different ways: on a period of 360 4-hourly time steps (90 days) and for a period of 1800 4-hourly steps (300 days). The main problem is related to poor quality of streamflow records during the summer periods; for some time intervals with no rainfall recorded the streamflow records are constant, with no decay. Figure 6.13 shows the calibration results for the period 3/01/1991-4/03/1991, where the efficiency statistic $E = 0.701$. The calibration results are not reasonable, but the deficiencies are related to the defects in streamflow recording which often exhibits a step-like behaviour. The calibration
Figure 6.13. Observed (solid line), modelled (dashed line) streamflow (cumecs) using a 4-hourly time step calibration for the Tallangatta Creek catchment (summer) over a 90 day period.
results obtained for the winter periods describe the streamflow processes well. Figure 6.14 presents the calibration fits obtained for the 90-day period of 5/07/1993-3/09/1993, with an efficiency statistic $E = 0.871$. The simulation results for this model over the 300-day period (5/07/1993-1/05/1994) are presented in Figure 6.15; the efficiency statistic for this simulation is $E = 0.868$. The calibration results obtained for this 300-day period gave similar results (Figure 6.16), with $E = 0.878$. In both cases the summer period with low flow are approximated poorly. This is related to the quality problem mentioned above for the summer flow data.

The 4-hourly modelled streamflow from the simulation results obtained over the period 5/07/1993-1/05/1994 for the were aggregated to a daily time step. Figure 6.17 shows the simulation on a daily time step, where the model identification was established on a 4-hourly basis. The efficiency statistic is $E = 0.899$, which is a much higher value than is usually achieved for model simulations using a daily time step.

6.5. Forecasting algorithms

6.5.1. Structure of the forecasting algorithm

The conceptual rainfall-runoff model IHACRES and a self-adaptive linear filtering approach were combined and applied for forecasting daily streamflow for nine catchments in the Upper Murray Basin (Table 6.1). Different types of models were considered in order to select the most appropriate forecasting algorithm. A disadvantage of rainfall-runoff models applied solely for forecasting purposes is that the residuals of the model are not white noise. The mean value of residuals of such models may be zero but the variance tends to change through time (eg seasonally) and residuals are strongly autocorrelated.
Figure 6.14. Observed (solid line), modelled (dashed line) streamflow (cumeecs) using a 4-hourly time step for the Tallangatta Creek catchment (winter) over a 90 days period.
Figure 6.15. Observed (solid line), modelled (dashed line) streamflow (cumecs) for simulation results using a 4-hourly time step for the Tallangatta Creek catchment over a 300 day period.
Figure 6.16. Observed (solid line), modelled (dashed line) streamflow (cumecs) using a 4-hourly time step for the Tallangatta Creek catchment over a 300 day period (calibration).
Figure 6.17. Observed (solid line), modelled (dashed line) streamflow (cumecs) using a 4-hourly time step for the Tallangatta Creek aggregated to the daily time step.
Linear filtering can be applied in order to decompose the residuals into a systematic component and white noise. The AutoRegressive Integrated Moving Average (ARIMA) model was selected here as an instrument for filtering the residuals.

Schematically, the model applied may be represented as a combination of two steps (Schreider et al., 1995):

1. The deterministic conceptual model IHACRES, providing for each time step (daily here) $k$ the modelled value of streamflow $y_k$ which can be expressed through its measured value $x_k$ as:

$$x_k = y_k + \xi_k,$$

where $\xi_k$ are the residuals. The discrete random function $\xi_k$ is strongly autocorrelated and its variance has seasonal fluctuations. Therefore it is logical to filter these residuals, or decompose them into a combination of systematic and white noise components.

2. The residuals of the IHACRES model $\xi_k$ are linearly filtered; the ARIMA model was used for this task.

6.5.2 Deterministic part (IHACRES)

The conceptual dynamic lumped parameter model IHACRES (see Section 2.4) has two modules: a non-linear loss module which transforms measured rainfall to effective rainfall using the temperature data, and a linear module defined as a recursive relation at time step $k$ for modelled streamflow $y_k$, computed as a linear combination of its previous values and excess rainfall. The loss module is used to account for the effect of antecedent weather conditions on the current status ($s_k$) of soil moisture and vegetation conditions, and
evapotranspiration effects. The effective rainfall \( u_k \) is calculated from the measured precipitation \( r_k \) and temperature \( t_k \) by formulae given in Section 2.2.4. When precipitation involves snow the snow melt (accumulation module, developed and applied in Chapter 4, can be used to generate equivalent rainfall for input to the above loss module.

The version of this model based on the Simple Refined Instrumental Variable (SRIV) technique for parameter estimation (see Jakeman et al. 1990) uses previous values of modelled flow for recurrent estimation of its value. An approach based on the Least Squares technique uses the previously measured values of streamflow in such recurrent relationships for estimating parameters. This latter method is not applicable for periods where the measured flow is unknown but can provide more accurate forecasts for periods where the observed data can be used to update predictions. The particular form of the linear module used in this work, which is based on the two parallel storages approximation (superposition of quick and slow flow recessions) is

\[
y_k = -a_1 y_{k-1} - a_2 y_{k-2} + b_0 u_k + b_1 u_{k-1}
\]

for the SRIV algorithm, where \( y_i \) is modelled streamflow, and

\[
y_k = -a_1 x_{k-1} - a_2 x_{k-2} + b_0 u_k + b_1 u_{k-1}
\]

for a so-called Least Squares algorithm, where \( x_{k-1} \) and \( x_{k-2} \) are previous measured values of flow. The total number of the parameters in this version of IHACRES, including its linear and non-linear modules, is six.
6.5.3. Stochastic part (ARIMA)

The residuals of the model \( \xi_1, \xi_2, \ldots, \xi_n \) were considered as the stochastic time series to be filtered. The ARIMA\((p,d,q)\) model can be defined by the following relations (Box and Jenkins, 1976; Bras and Rodriguez-Iturbe, 1985):

\[
\phi(B) ((1-B)^d \xi_t - D) = \theta(B) \alpha_t,
\]

where \( B \) is a backward shift operator such that \( B \xi_t = \xi_{t-1} \), \( (1-B)^d \) is the difference operator, \( D \) is the mean value of the differenced series and \( \phi(B), \theta(B) \) are the polynomial expressions for \( p \) autoregression and \( q \) moving average values:

\[
\phi(B) = 1-\varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p
\]

\[
\theta(B) = 1-\theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q
\]

Modelling of seasonal periodicity was excluded from consideration here. The sum \( p+q+d \) defines the number of parameters for the stochastic module to be optimised.

6.5.4. Application of the ARIMA model

Linear filtering of the errors of the conceptual model IHACRES was undertaken using moving windows, each with a duration of 40 days and a 1 day timestep. The ARIMA models were calibrated separately on each window and the forecasts of the residuals for \( L \) days forward were calculated. The statistical significance of the approximation was controlled for each step using the Box-Ljung portmanteau statistic (McLeod, 1978).

In order to test the forecast procedure, it was assumed that the rainfall for \( L \) days forward is known; see expressions (6.1) and (6.2).
The residuals of the SRIV and Least Squares versions of the IHACRES conceptual model were used as inputs for the linear filtering algorithm. To assess how informative these prediction algorithms are, an additional test was suggested: the residuals of the "naive" forecasting algorithm, where the predicted value of stream flow is equal to the streamflow at the previous time step \( y_k = x_{k-1} \), were also considered to provide forecasts of streamflow.

A range of different ARIMA structures was considered with each deterministic model (SRIV, Least Squares and "naive") to select the best forecasting algorithm. The values for the number of autoregressive parameters \( p \), moving average parameters \( q \) and differencing \( d \) were limited to a maximum of 2, 2 and 1, respectively, in order to avoid overparameterisation. Values (0,0,0) correspond to the conceptual model itself, when considered as a forecasting algorithm.

6.5.5. Results and analysis

Table 6.10 summarises the results of testing the different optimal parameters in each \((p,d,q)\) on the two year calibration period (1980-1981) for Tallangatta Creek. The values of mean absolute and mean square errors for one day ahead forecasts calculated over this two year period were selected as a measure of the quality of the model identification. The model was considered to fail if it diverged for more than 5% (35 of approximately a 700 day period) of the windows. The best results were provided for ARIMA structures (1,0,0) and (1,1,0).

Figures 6.18 and 6.19 show the results of SRIV IHACRES performance on the periods of low and high flow, respectively, and their improvements after filtering by an ARIMA process.

Table 6.11 illustrates how the quality of forecast depends on how many days forward \((L)\) it is provided. The results are illustrated for two catchments for Tallangatta and Cudgewa Creeks, respectively. The results show that the quality of forecast obtained by linear filtering of the residuals is better than the forecast obtained by using the conceptual model solely, for values
Figure 6.18. 1-day ahead forecast for a low flow period in the Tallangatta Creek catchment.
Figure 6.19. 1-day ahead forecast for a high flow period in the Tallangatta Creek catchment.
of $L$ up to 3 (the Cudgewa Creek) and 5 (the Tallangatta Creek). The results of the forecasting algorithm application to all the catchments considered are summarised in Table 6.12. The efficiency statistics and bias for the IHACRES model applied solely are presented.

Table 6.10. The mean absolute and mean square forecast errors obtained for a range of ARIMA parameters and three different conceptual models. "*" means model diverges.

<table>
<thead>
<tr>
<th>(p,d,q)</th>
<th>SRIV</th>
<th>Least Squares</th>
<th>&quot;Naive&quot; model</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0,0,0)</td>
<td>1.02; 3.58</td>
<td>0.82; 7.57</td>
<td>0.73; 5.12</td>
</tr>
<tr>
<td>(1,0,0)</td>
<td>0.65; 2.34</td>
<td>0.85; 7.24</td>
<td>0.75; 5.71</td>
</tr>
<tr>
<td>(0,0,1)</td>
<td>0.89; 3.13</td>
<td>*</td>
<td>0.79; 6.00</td>
</tr>
<tr>
<td>(2,0,0)</td>
<td>0.69; 2.59</td>
<td>0.82; 6.80</td>
<td>0.79; 6.00</td>
</tr>
<tr>
<td>(1,0,1)</td>
<td>0.74; 2.81</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>(1,1,0)</td>
<td>0.65; 2.60</td>
<td>1.22; 15.50</td>
<td>1.00; 9.80</td>
</tr>
<tr>
<td>(0,1,1)</td>
<td>0.70; 2.60</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>(1,1,1)</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>(1,2,0)</td>
<td>0.90; 5.23</td>
<td>2.05; 38.42</td>
<td>1.46; 20.15</td>
</tr>
<tr>
<td>(2,1,1)</td>
<td>0.67; 2.55</td>
<td>1.16; 11.88</td>
<td>0.99; 9.07</td>
</tr>
<tr>
<td>(2,2,0)</td>
<td>0.89; 4.54</td>
<td>1.72; 24.49</td>
<td>1.32; 15.64</td>
</tr>
</tbody>
</table>

Table 6.11. The quality of forecast obtained for the linearly filtered ARIMA(1,0,0) residuals of the conceptual model SRIV IHACRES. The mean absolute and mean square errors are given.

<table>
<thead>
<tr>
<th>$L$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Tallangatta Creek</td>
<td>0.65</td>
<td>0.81</td>
<td>0.92</td>
<td>0.96</td>
<td>1.03</td>
</tr>
<tr>
<td></td>
<td>2.34</td>
<td>3.27</td>
<td>3.35</td>
<td>3.47</td>
<td>3.58</td>
</tr>
<tr>
<td>The Cudgewa Creek</td>
<td>0.63</td>
<td>0.74</td>
<td>0.75</td>
<td>0.76</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>2.50</td>
<td>2.80</td>
<td>2.80</td>
<td>2.86</td>
<td>2.64</td>
</tr>
</tbody>
</table>

for the periods specified in Sections 6.2 and 6.3. The selection in different catchments of different periods for simulation run tests is explained by the availability and quality of rainfall data for these sites. The combined forecasting algorithm was applied for the whole period of
availability of streamflow records. For periods when precipitation is not recorded it provides forecasting values using information about streamflow solely. Even for this case, the comparison illustrates the considerable improvement obtained after application of the linear filtering procedure to the residuals of the IHACRES model, including in the case of the

Table 6.12. Efficiency statistics \((E)\) and Bias for long-term simulations period for all 9 catchments considered. The results of the IHACRES simulation and IHACRES combined with an ARIMA algorithm are presented.

<table>
<thead>
<tr>
<th>Station number</th>
<th>River and station location</th>
<th>IHACRES model applied solely</th>
<th>IHACRES model combining with ARIMA ((1,0,0))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(E)</td>
<td>Bias</td>
</tr>
<tr>
<td>401203</td>
<td>Mitta-Mitta River at Hinnomunjie</td>
<td>0.669</td>
<td>0.50</td>
</tr>
<tr>
<td>401220</td>
<td>Tallangatta Creek at McCallums</td>
<td>0.611</td>
<td>0.35</td>
</tr>
<tr>
<td>401208</td>
<td>Cudgewa Creek at Berringama</td>
<td>0.638</td>
<td>0.62</td>
</tr>
<tr>
<td>401012</td>
<td>Murray River at Biggara</td>
<td>0.649</td>
<td>0.37</td>
</tr>
<tr>
<td>401217</td>
<td>Gibbo River at Gibbo</td>
<td>0.692</td>
<td>0.63</td>
</tr>
<tr>
<td>401210</td>
<td>Snowy Creek at Granite Flat</td>
<td>0.729</td>
<td>0.06</td>
</tr>
<tr>
<td>401013</td>
<td>Jingellic Creek at Jingellic</td>
<td>0.533</td>
<td>0.17</td>
</tr>
<tr>
<td>401014</td>
<td>Tooma River at Pine Grove</td>
<td>0.664</td>
<td>0.98</td>
</tr>
<tr>
<td>401216</td>
<td>Big River U/S of Joker Ck</td>
<td>0.709</td>
<td>-0.18</td>
</tr>
</tbody>
</table>

Jingellic Creek catchment, where inferior deterministic modelling related to its ephemeral nature exists (see Section 6.2).
6.6 Discussion and conclusions

Successful calibration of modelled streamflow was performed for nine rivers of the Upper Murray Basin on a daily basis and for Tallangatta Creek on a 4-hourly time step. The results described above show that the IHACRES model provides consistently good results for both snow-free and snow-affected catchments in the Upper Murray Basin.

The results obtained for the catchment of Tallangatta Creek showed that during the winter periods 4-hour time step calibration provides results better than the results obtained on the daily time-step basis. Our simulation test for the model calibrated on the 4-hourly time step provides an efficiency value $E$ of about 0.900, when the streamflow data were aggregated to a daily basis. This provides considerable improvement of the model performance compared with the result obtained for daily time-step calibration where $E$ is about 0.600 - 0.700. However, the poor quality of 4-hourly streamflow data recorded for Tallangatta Creek during summer periods at present does not allow the use of this approach for periods of low flow.

The method of combining a conceptual rainfall-runoff model and a self-adaptive linear filtering approach was developed and applied to forecast streamflow for nine catchments in the Upper Murray Basin. Considerable improvement compared with prediction based on the use of the conceptual model only was achieved: the errors of the forecast 3-5 day forward for the combined method are comparable with the errors of a 1 day forward prediction provided by the conceptual model only. A $(1,0,0)$ structure for the ARIMA algorithm was selected as the most appropriate overall for forecasting in the region under consideration. This allows the use of a combined deterministic and self-adaptive stochastic approach for better approximation of river discharge and for operational forecasting, in particular for reservoir management.
CHAPTER 7

CONCLUSIONS

Summary

The structure, rationale, methodology and general conclusions of the thesis are presented in this chapter. Several suggestions about fruitful continuation of the research undertaken in the thesis are also proposed.

7.1. General structure of the work implemented

The analysis implemented in the thesis consists of four major parts:

1. Identification and testing was undertaken of an appropriate rainfall-runoff model for the catchments of interest allowing prediction of stream discharge in relation to climate. The lumped conceptual rainfall-runoff model IHACRES was selected as the basic modelling tool and was found to perform well across all hydroclimatologies whose average annual yield characteristics ranged from 10% (Sugarloaf Creek) to 60% (the Acheron River). Assessment of the accuracy of the model for stream discharge prediction or incorporation in climate models for present-day simulations was undertaken. The potential for increases in the spatial scale of the individual catchment modelling was illustrated for the Goulburn Basin.

2. Assessment was performed of the impacts on runoff and extreme events, such as droughts and floods, in the region due to a range of historical climate variations and
climate change scenarios associated with the enhanced greenhouse effect. This assessment was undertaken for snow-free, as well as for snow-affected regions.

3. Development was accomplished of a snow melt/accumulation module, consistent with the complexity of the rainfall-runoff model IHA\textsc{res} and the input climate data available, in order to calculate the equivalent precipitation inputs for IHA\textsc{res} in the snow-affected catchments.

4. Development was also achieved of a stochastic component of an operational flood forecasting system in order to support reservoir management in the Upper Murray Basin, where Australia's two large reservoirs, Lakes Dartmouth and Hume, are located. ARIMA linear filtering was implemented, as a basic method adjunctive to IHA\textsc{res}, for developing the forecasting algorithm.

7.2. Rationale

The upper Basins of the Murray-Darling Drainage Division (MDDD) contribute a large portion of the water consumed in the agricultural region of the Murray Valley. The Upper Murray, Kiewa, Ovens and Goulburn Basins together provide more than 9,200,000 ML of annual flow. This amount constitutes about 95% of the total discharge of Basins in the Victorian part of the MDDD, and more than 40% of the total water resources of the state of Victoria, which is 22,500,000 ML annually (Water Victoria, 1989). Three major water reservoirs are located in this area: Lake Eildon (in the Goulburn Basin), Lake Hume and Lake Dartmouth (both the latter are in the Upper Murray Basin) with a storage capacity of 3,390,000 ML, 3,038,000 ML and 4,000,000 ML, respectively. One of Australia's largest irrigated regions is the Goulburn-Murray Irrigation District. It is located in the area of the Loddon, Campaspe, Goulburn and Broken Basins, and is almost completely irrigated using surface water resources.
Analysis of surface water resources in the region in relation to climate forcing is extremely important for water planning and is one the main objectives of this work. The nature of possible climate changes is a temperature increase (global warming effect) and less certain changes in precipitation. Future climate changes may bring an additional significant variation in water supply, with associated effects (e.g. Jakeman, 1990) on demand for water and other related resources. Reduction of water availability can lead to an increase in water use conflicts, causing serious socioeconomic problems. Increases in water availability, on the other hand, may create new economic opportunities. Knowledge of the impacts of possible climate changes on water resources may aid the taking of objective and informed decisions about the operation of these resources. In addition to long term runoff volumes, changes in rainfall and its variability may exacerbate floods, droughts, channel erosion, recharge to aquifers and salinisation of water. Estimation of peak streamflow is especially important because, although there is some uncertainty about the frequency of low rainfall events under climate change, it is probable that the intensity of large rainfalls will increase with future global warming (Fowler and Hennessy, 1995). An analysis of potential changes in streamflow requires a special effort in some Australian regions. Because of their high level of flow variability, they are sensitive to minor changes in their climatic forcing. It turns out that this higher sensitivity is the case in a minority of catchments selected here, such as the Sugarloaf Creek catchment in the Goulburn Basin.

7.3. Methodological aspects

The conceptual rainfall-runoff model IHACRES requires input climatic time series (precipitation and temperature) and yields as output modelled streamflow and, accordingly, losses related to evapotranspiration and ground water infiltration. The IHACRES
methodology for predicting streamflow discharge in a catchment can be structured in four steps:

1. Calculation of rainfall excess (or effective rainfall) from measured precipitation using a non-linear transformation that takes into account basic catchment loss dynamics: a time constant reflecting the rate of drying of the catchment at $20^\circ C$ ($\tau_w$) and a factor ($f$) modulating this rate as temperature varies.

2. Approximation of measured streamflow as a linear convolution of the unit hydrograph with rainfall excess. The approximation technique is based on use of a simple refined instrumental variable (SRIV) method of parameter estimation discussed by Jakeman et al. (1990).

3. Simulation or validation tests which quantify the reliability of the approximation on time periods different to that on which calibration was performed. The best set of model parameters is conditionally selected at this stage, primarily by maximising the model efficiency (percent of variance explained by the model) and minimising bias (mean absolute error). However, other criteria, such as the average estimated parameter variance and the cross correlation between model residuals and model outputs, are considered in order to ensure that model uncertainty is reasonable and that there is no substantial systematic relationships between these two quantities.

4. Analysis of the accuracy of the model's sensitivity to precipitation and temperature. Primary checks are the correspondence between historical and modelled annual discharge and historical and modelled long term average monthly discharge. The latter helps ensure a calibrated model is appropriately sensitive to changes of the order of 2-3$^\circ C$ experienced on average between adjacent months.
Two different approaches for estimating climate impacts by lumped conceptual models such as IHACRES can be defined, according to Jakeman et al. (1995) and Oglesby et al. (1995). These are a fast track approach and long-term approach. In the fast track approach it is proposed that conceptual models such as IHACRES are calibrated using precipitation and temperature data for a particular catchment, then the series are transformed according to broad hypothetical climate scenarios (or those generated by some climate and/or weather simulation models are used), and used as an input for the rainfall-runoff model in order to calculate the corresponding runoff scenarios. Two main advantages of the fast track approach can be emphasised. Firstly, it provides a set of model parameters which can be used for categorisation of catchments with different hydrologic response properties and, hopefully, related physical catchment descriptors (PCDs). PCDs reflect the landscape attributes and vegetation cover in catchments. Secondly, this approach also provides useful information about what types of catchments are more problematic for the model identification, indicating where improvements in model performance are necessary. It tests the need for description of more complicated interactions between climate models and IHACRES, including the need for smaller scale modelling of the heterogeneity of catchment response.

The fast track approach to climate modelling can now be applied using the parameterisations of hydrological response obtained in the present work, along with techniques for downscaling precipitation and interpolating daily evapotranspiration outputs, calculable from the IHACRES model, to sub-daily time steps required by climate models.

The parameterisations are applicable strictly to present-day climate and vegetation conditions. In the long term approach, physical descriptors of catchments affecting hydrological response are developed in order to circumvent the empirical calibration of the model discharge against the observed streamflow data in the fast track approach. This is necessary when stream gauge data are not available or when it is desired to examine hydrological response under
future conditions involving changes in vegetation. The long term approach also allows the effects of appropriate small-scale heterogeneity in the land surface and hydrological response to be incorporated. In this case all parameters of the IHACRES model must be related to the PCD values. The main problem associated with this approach of course is related to establishing the relationships between model parameters and PCDs. This problem is known as 'regionalisation' and was studied with encouraging results, for IHACRES, by Post et al. (1996), Post and Jakeman (1996), Sefton et al. (1993) and Sefton and Boorman (1996). However, much more work in many regions is needed to develop a synthesis of collective relationships for the long term approach. Bates (1994) provides a review and critique of regionalisation.

The climate impact analysis undertaken in the thesis can be separated into two aspects: climate impacts on the mean monthly and annual discharge, and climate impacts on the probability of extreme events such as droughts and floods. The analysis of impact in both cases was performed for two dates in the future (2030 and 2070).

There is substantial uncertainty in the magnitude, timing and spatial distribution of climate change. One approach proposed by CIG (1992) was to analyse five different General Circulation Models, considered acceptable for their relative verisimilitude with respect to the Australian continent, and generate climate scenarios for each, thereby providing a range of possible changes in temperature and precipitation. Following this approach, two extreme cases of possible future mean climatic characteristics were considered for the present work: an optimistic scenario, reflecting a minimum reduction or, possibly, an increase in river discharge (the 'most wet' scenario) and a pessimistic or 'most dry' scenario, where discharge is reduced maximally. These two cases might be considered as endpoints in the interval containing possible climate impacts on surface runoff.
Limitations of this approach are described by Bates et al. (1994). The direct transformation of historical climate records, using GCM outputs according to changes in mean values, in order to estimate possible climate impacts may be considered improper due partly to the coarse resolution of GCM spatial grids and the simplified GCM representation of land surface-atmosphere-ocean interactions. The use of stochastic models representing daily weather variations at the site of the hydrological model application is an alternative approach to estimate possible climate impacts on streamflow. This approach, developed for the Australian region, is described in Bates et al. (1993), Bates et al. (1994) and Charles et al. (1993). A major additional advantage of this approach is that the correlation structure among the different climate variables simulated is realistic, at least in terms of historical climate. The use of Limited Area Models (LAMs) with higher than GCM spatial resolution, when a LAMs grid area is comparable with the areas of catchments (0(100) km²) considered for runoff modelling, is another possible adjunctive solution to this problem (McGregor and Walsh, 1993, 1995).

Especially for forecasting purposes, all hydrological processes, such as rainfall, streamflow, evaporation and infiltration, are, to some extent, random processes. Therefore, the theory of random processes can contribute to our knowledge about the nature of these processes. In other words, they can be considered as a stochastic processes. The IHACRES model is a deterministic approximation of stochastic time series of streamflow. Thus, the model error is also a random function. However, this error is strongly autocorrelated. It can be illustrated by the following example: if a peak flow value is underestimated/overestimated, it is likely then that several subsequent model values will also be less/greater than observed streamflow. The methodology used here for operational streamflow forecasting is based on the idea of decomposition of model errors a the sum of systematic and white noise components. Linear filtering algorithms can be applied for these purposes. The AutoRegressive Integrated
Moving Average (ARIMA) model was selected as an instrument for filtering the deterministic model residuals.

### 7.4 Inventory of results

a) *The rainfall-runoff model.* It is perhaps the first time that a conceptual rainfall-runoff model, and certainly that IHACRES, has been applied and comprehensively tested in contiguous subcatchments totalling such a large area involving several Basins. For the major catchments gauged for discharge in four Basins in eastern Victoria, the IHACRES model has been calibrated and conditionally validated on a daily time step, its accuracy having been quantified on historical periods independent of the calibration. The model provides good performance in snow-free areas of the major headwaters of the Goulburn and Ovens Basins, as well as in snow-affected catchments of the Kiewa and Upper Murray Basins. The total drainage area of these four Basins is 41,900 km² and their total mean annual discharge is 9,285,000 ML. The important result is that the IHACRES model can be used to model daily streamflow effectively and (parameterically) efficiently over a wide range of catchment sizes.

Successful calibrations of the rainfall-runoff model were performed for 27 rivers contributing streamflow to the Goulburn, Ovens, Kiewa and Upper Murray Basins. The total discharge of the rivers modelled constitutes approximately 5,583,000 ML or 60% of the total discharge of the four Basins. The total area of these catchments modelled is 13,537 km². The models were evaluated by simulation tests over the entire common period of observation for all catchments considered. The results of these tests provided a reasonably low volumetric error. The mean relative errors in annual discharge, calculated for a simulation run over the whole period of streamflow recording for the three groups of snow-free catchments (upper and lower parts of the Goulburn Basin and the Ovens Basin) are from 5% to 8%.
The appropriate spatial extent for any catchment area under modelling consideration will be determined principally by the adequacy of the precipitation data used to represent the areal cover of the catchment being modelled. The actual underlying response dynamics of a catchment also affect the predictive performance of the model. In particular, large slowflow (or baseflow) proportions (> 0.60 approximately) permit better model fits to the discharge data (Hansen et al., 1996). In all cases, the catchments modelled were at small enough scale to yield good predictive results. However, the methodology for calibration and validation can identify if a smaller scale is required. It is also possible to model some of the catchments at a large scale as was demonstrated for five catchments in the Goulburn Basin, which could be modelled as one composite catchment.

b) Snow melt/accumulation. The problem of snow runoff modelling has been considered for catchments in the Australian alpine region. A snow melt/accumulation model was developed to provide an equivalent rainfall input for the conceptual rainfall-runoff model IHACRES which was used for the subsequent runoff modelling. The snow melt/accumulation model is based on a modified degree-day approach wherein the parametric efficiency is compatible with that of IHACRES. The model provides the equivalent amount of melted/accumulated water for each gridcell of the catchments under consideration with a spatial resolution of 2.5 km x 2.5 km. The method allows modelling of the melt/accumulation processes directly without recourse to information about current snow cover distribution in the area, which is especially advantageous for regions with a lack of observational snow data. The combined precipitation-runoff model was applied to the snow-affected catchments of the Mitta-Mitta, Kiewa, Upper Murray, Gibbo and Big Rivers and for the Snowy Creek catchment. This is also the first time a precipitation-runoff model has been applied in Australia on a daily basis to a snow-affected area. The calibration and validation results show that the model performs with about the same predictive efficiency for
snow-affected as for snow-free catchments. The mean relative errors in annual discharge, calculated for a simulation run over the whole period of streamflow observation for the snow-affected areas, are almost the same as those for snow-free areas: for instance, for the snow-affected catchment of the Kiewa River this error is 7%.

c) Climate impact: runoff. The effect of historical climate variability on streamflow and a catchment wetness index has been investigated. Under some assumptions, the models can be used as a basis for estimation of the potential impact of climatic change on water availability for irrigation and on the frequency distribution of extreme events such as floods and droughts. Climate scenarios developed for the Australian region were employed for estimating the possible climate impacts on water availability in these Basins. Two extreme cases were considered: a ‘most dry’ scenario yielding a minimum amount of river runoff and a ‘most wet’ scenario yielding a maximum amount. These two cases might define the lower and upper limits respectively for total discharge of the rivers in the region considered under the enhanced greenhouse effect. For two dates in the future, 2030 and 2070, the associated reduction in annual discharge for the ‘most dry’ scenario reaches 28% - 38% and 53% - 64%, respectively; the amount of available water decreases more in snow-free catchments than in snow-affected regions, although the difference between these two types of catchments is small. The ‘most wet’ scenario provides slightly different impacts for snow-free and snow-affected catchments: it is negligibly small (between a 3% reduction and a 4% increase at 2030 and 0% - +6% at 2070) for snow-free areas, whereas it is considerably higher for snow-affected Basins: an 11% increase for the Kiewa catchment and a 17% increase for Mitta-Mitta at 2030; and a 21% and 12% increase for these catchments at 2070, respectively.

d) Climate impact: extreme events. For snow-free catchments, flood frequency, defined as streamflow events with daily discharge higher than 50 cumecs, was found to increase for the ‘most wet’ scenarios; 41% at 2030 and 81% at 2070. The important fact is that little
The very high level of uncertainty should be indicated here. For instance, for the Kiewa River catchment flooding may increase to 62% for the ‘most wet’ scenario in 2030, whereas flow events higher than the selected magnitude may almost vanish for the ‘most dry’ scenario.
increase in the absolute value of flow provides considerable increase in the probability of high flow events (defined as events higher than a 50 cumecs). The probability of high flow for the 'most dry' scenarios rapidly decreases from 0.022 at present to 0.004 at 2030 and to a zero value at 2070 for snow-free catchments. The increase in probabilities for the snow-affected Kiewa Basin (also defined for a 50 cumecs threshold) in the case of the 'most wet' scenarios is from 0.079 at present, to 0.096 at 2030 and 0.114 at 2070, which correspond to 22% and 44%, respectively. As the absolute value of discharge is more than 2 times higher in the Kiewa than in the Upper Ovens River, another threshold may be chosen for definition of 'floods' in the Kiewa Basin. If 'floods' are defined as streamflow events with discharge higher than 65 cumecs these probabilities increase to 0.039 and 0.053 at 2030 and 2070, respectively. This corresponds to a 62% and 120% relative increase at these dates. (The probability of such events, 0.024 at present, is almost the same as the probability of streamflow events with discharge greater than 50 cumecs for the Upper Ovens). The general conclusion is that predicted high flow probabilities are slightly higher for snow-affected catchments, but future can be summarised as being about 50% at 2030 and 100% at 2070 for both types of catchments. The probability of high flow events in the 'most dry' scenarios for the Kiewa catchment reduces to values of 0.018 and 0.002 at 2030 and 2070, respectively.

Drought frequency, as defined by a soil wetness index, increased 35% for the 'most dry' scenario at 2030 and 80% for the 'most dry' scenario at 2070 for snow-free areas and, similarly, 36% and 87% for the snow-affected Kiewa River. The similarity of results received for snow-free and snow-affected regions naturally corresponds to the fact that even in alpine areas snow processes are negligible in the summer period.

The models, selected for each of the catchments, were used for estimation of future climate impact under the assumption that overall vegetation effects on runoff in the area considered
will remain similar to that of recent history. Considerable changes in land use or deforestation in this area in future may provide more dramatic changes in discharge in these Basins. However, it was argued in Chapter 1 that there is little likelihood of logging in these largely protected catchments, that bushfire effects will be either limited spatially or temporally, and that increases in natural forest cover above the tree line will not be considerable over the next 70 years. It was also suggested that the effects of elevated carbon dioxide levels on vegetation response have not yet been well quantified, especially at catchment scale, and that perhaps over the time frame of our projections are not likely to be substantial. The major limitation of the approach suggested is related to the high level of uncertainty in the estimated climatic patterns, mirrored in the large differences in streamflow values associated with the selected scenarios. Application of information obtained by Global Climate Models with higher spatial resolution or by Limited Area Models, developed for the region considered, in conjunction with weather simulation models, is one way to seek more accurate estimation of streamflow events in the future.

e) 4-hourly time step modelling. The results obtained for the catchment of Tallangatta Creek, where model identification was undertaken on both a 4-hourly and daily time step, showed that during the winter periods the 4-hourly modelling provides results better than those obtained on the daily time step. A simulation/validation test for the model calibrated on the 4-hourly time step provides an efficiency value $E$ of about 0.900, when the modelled streamflow time series is aggregated to a daily basis. This provides considerable improvement in model performance compared with the result obtained using the direct daily time step calibration where $E$ is about 0.600-0.700. However, the poor quality of 4-hourly streamflow data recorded for Tallangatta Creek during summer periods does not allow the use of this approach for periods of low flow. Therefore, whether or not potential predictive
improvements in modelling at a 4-hourly time step are to be realised in this region will depend upon the quality of the 4-hourly records for the catchment in question.

f) Operational streamflow forecasting. A method of combining a conceptual precipitation-runoff model (with optional snow melt/accumulation module) and a self-adaptive linear filtering approach was developed and applied to forecast streamflow for nine catchments in the Upper Murray Basin. Considerable improvement compared with prediction based on the use of the conceptual model only was achieved: the errors of forecasts 3 to 5 days forward for the combined method are comparable with the errors of a 1 day forward forecast provided by use of the conceptual model only. The (1,0,0) structure of the ARIMA algorithm, that is a simple first-order autoregressive stochastic model with one parameter to be estimated, was selected as generally the most appropriate for forecasting in the region under consideration.

This allows the use of a combined deterministic and self-adaptive stochastic approach (with 7 parameters in the snow-free case and 10 parameters in the snow-affected case) for better approximation of river discharge and for operational forecasting, in particular for reservoir management.

7.5. Future work

The major part of the four Basins' discharge which has not been modelled in this work (about 32% of total discharge for the Goulburn, 39% for the Ovens, 28% for Kiewa and 61% for the Upper Murray Basins) is contributed by the ungauged areas of this region. In order to predict the hydrological response over the entire region, a long term approach or regionalisation could be attempted by relating the already derived IHACRES model parameters to landscape attributes throughout the gauged catchments in order to predict streamflow in the ungauged catchments. The combination of results obtained for the IHACRES application in this area, snow melt/accumulation modelling, and the regionalisation
approach which could be developed for the ungauged catchments is a step towards acquiring
a comprehensive set of analytic tools for examining the water regime in the region under
different conditions such as versions climatic and land use scenarios.

This future work could be structured in three steps:

1. Comprehensive modelling of stream discharge in the Upper Murray Basin could be undertaken down to the inlets of the Hume and Dartmouth Reservoirs. This includes identification of model parameters for the gauged and ungauged catchments upstream of these Lakes and application of flow forecasting methods in order to support reservoir management. A 4-hourly forecasting time step would be useful as a basis for the modelling providing reliable observations are available. Different flood forecasting techniques could also be tested during this stage of the work. Kalman filtering would be a strong candidate as it allows recursive updating of the conceptual model parameters, while the ARIMA method allows updating of the stochastic component of the model. However, it may eventuate that such additional complexity is unwarranted.

2. Estimation of climate impact on streamflow availability for irrigation, and development of adequate models of changes in demand for irrigation according to different climatic conditions is proposed, taking into account possible changes in plant water use efficiency and irrigation demand for assessing availability of water. Such comprehensive streamflow and demand modelling is especially important for the Goulburn Basin because water from this Basin is exported to three adjacent Basins (Broken, Campaspe and Loddon), where it is used for irrigation needs, in the Murray-Goulburn irrigation district in particular.

3. Extension of the region under study seems warranted given the results obtained in the thesis. Other Basins of the MDDD are also very important for water supply in this area.
Large scale hydrologic response modelling in the Murrumbidgee, Campaspe and Loddon Basins of the MDDD, as well as, in the Snowy River Basin of the South East Coast Division is a logical continuation of the work.
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