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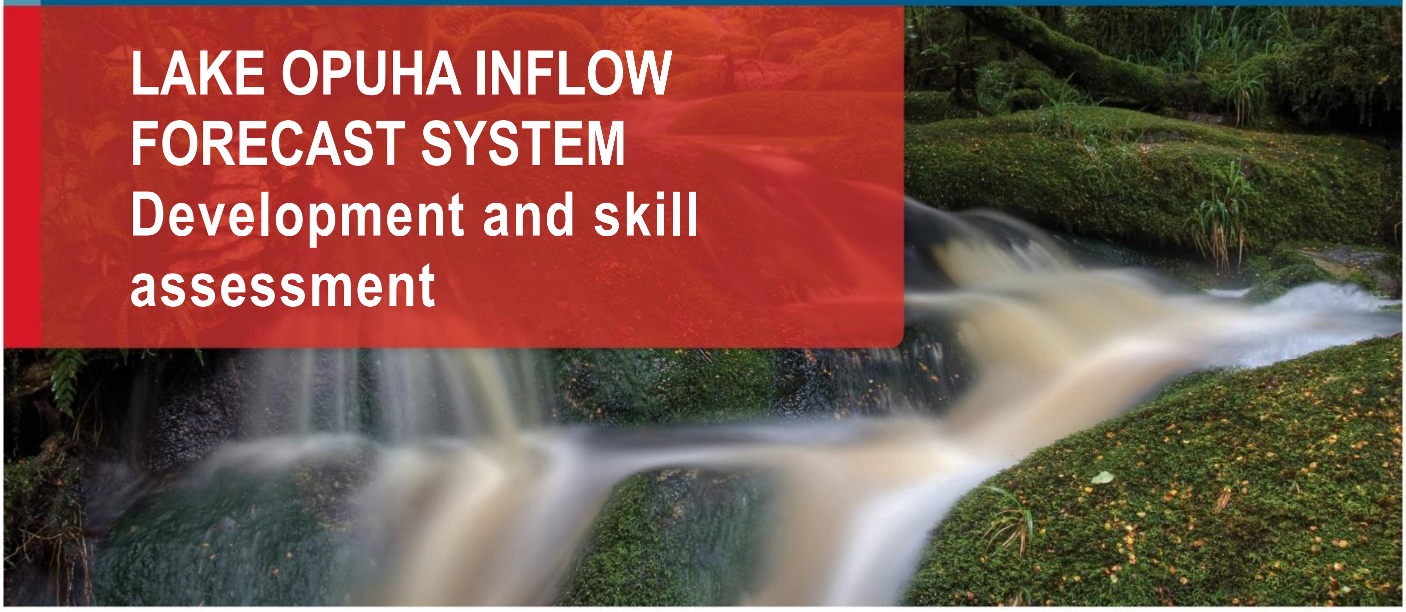
Water Management REPORT

LAKE OPUHA INFLOW FORECAST SYSTEM Development and skill assessment



PREPARED FOR
Environment Canterbury and Opuha Water Ltd.

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EXECUTIVE SUMMARY

A forecast system of monthly Lake Opuha inflows has been prepared. It provides estimates of the likelihood of the inflows being within various ranges. In addition, a single value, best-guess average inflow forecast is provided. Forecasts were simulated for the last thirty years and compared to the observed inflows and the long-term average inflows to determine if they have skill. Forecasts were generated at 1 to 6 month lead times, from July until November.

The probability forecasts were better at predicting the inflows, compared to the long term average, for August, September, October and December. November forecasts were worse than the long term average and show no skill.

The single-value forecasts show skill for September and December that is unlikely to be a result of pure chance.

At the height of the winter snow storage season (on average in Late August) the long term median is estimated to be 22 Mm^3, the equivalent of 1/3 of the volume of Lake Opuha. While a considerable amount of snow falls in the winter months, a great deal of melt occurs throughout the winter as well. Only of a portion of the snow that falls persists as frozen water storage for more than a month.

The snow model was tested on limited elevation ranges to see how this affects the forecast skill. Imposing elevation limits reduced the skill of the 1 and 2 month lead time probability forecasts, but improved the skill of the 3, 4 and 5 month lead time probability forecasts for December and January.

For 2017, at the end of August, the total snow storage is at the median level. Inflow forecasts for September and October indicate near-equal chance of flows at the different flow bands, but a slightly increased chance of flows in the lowest 20th percentile for December.

Recommendations

To assist with planning, it is recommended that the current snow storage estimate graphs be amended to include a water storage volume scale.

The results of the forecast skill assessment indicate that the forecasts contain useful information. Implementation of an operational seasonal inflow forecasting system to run weekly from July through to November would enable this information to be provided every year in a timely manner to assist with water management.

The forecast skill tests indicate the model is not providing an accurate reflection of the catchment hydrology. The model currently operates using default model parameters. Tuning the model parameters to the Lake Opuha catchment would provide a pragmatic first step towards lifting the forecast skill scores, particularly for November.

1 BACKGROUND

The ability to forecast the water flowing into Lake Opuha would assist with management of the related irrigation schemes and the downstream rivers.

Since 2015, Aqualinc has been generating daily estimates of the amount of snow stored in the Lake Opuha catchment. It is thought that years with large end-of-winter snow storage lead to generally higher lake inflows, and that years with low snow storage generally have lower lake inflows. In this way the snow storage estimates are used as a proxy for spring inflows.

The melting of the snow is primarily controlled by air temperature. To forecast snow melt, temperatures from previous years for the forecast months of the year may be used to prepare a first guess of how much of the currently-observed snowpack will melt. Applying a range of historic temperatures, from different years, leads to a range of forecast snow melt scenarios. This range can be used to determine the likelihood of flows being at a certain level.

As well as snow melt, inflows come from rain. Knowledge of the size of the winter snow storage has no predictive ability for the inflows originating from rain. For this reason, inflow forecasts based on snow storage have a high degree of uncertainty. It is assumed that for some months of the year, and for certain lead times, forecasts based on snow melt provide useful information. For efficient use of the forecasts it is necessary to identify the times of year, and the lead times for which the forecasts add value.

Currently the snow storage is estimated relative to the long term averages, not as an absolute value of the amount of water. Through comparison of modelled snow melt and rainfall to lake inflows, a relationship between the two may be established. This enables the snow storage estimates and forecasts to be provided in terms of lake inflow quantities. Establishing this relationship also helps with understanding how important the snowmelt is to total lake inflows.

Currently the snow storage is provided for the entire Lake Opuha catchment. It is only the higher areas of the catchment that retain snow for any length of time. For snow storage, these higher areas are more important. The elevation, above which the snow storage estimates lead to the best forecasts, needs to be identified.

This report outlines:

1. the preparation of the snow storage forecasts,
2. the identification of when the forecasts have value,
3. the quantification of snow storage in terms of potential inflow and
4. the optimisation of the elevation limit for snow storage estimates

This is the second of three related reports. The other two overview:

- the impact of climate cycles and trends on the headwaters of the Opihi, Opuha and Orari[1], and
- snow storage climate change scenarios[2]

[1] Released in draft to ECan in June 2017. Currently under revision following ECan review.

[2] Scheduled for delivery in October 2017.

2 LAKE INFLOW FORECASTING

Summary

Forecasts of the probability of inflows being within set flow ranges were prepared. This was done through running the Lake Opuha Snow Storage model, initialised with the latest estimate of snow storage, into the future driven by climate data from previous years. The model provides a series of alternative future total rainfall-plus-snow-melt.

A single value forecast is also provided, based on the median of the alternative futures.

Details

The basis of the Lake Inflow forecasting system is the Lake Opuha Snow storage estimation system.

All data processing is undertaken in "R"[3].

2.1 Lake Opuha Snow Storage Estimation System

The Lake Opuha Snow Storage Estimation System provides daily estimates of the amount of snow within the Lake Opuha catchment. The snow quantity is provided as a relative measure with respect to the long term median. The estimates are emailed to Opuha Water Ltd. once a week during the winter months as a graph, and as a table of values. The Graph is also provided online at rainfall.nz/OWL/OpuhaSnow.html. An example of the graph is shown in Figure 1.

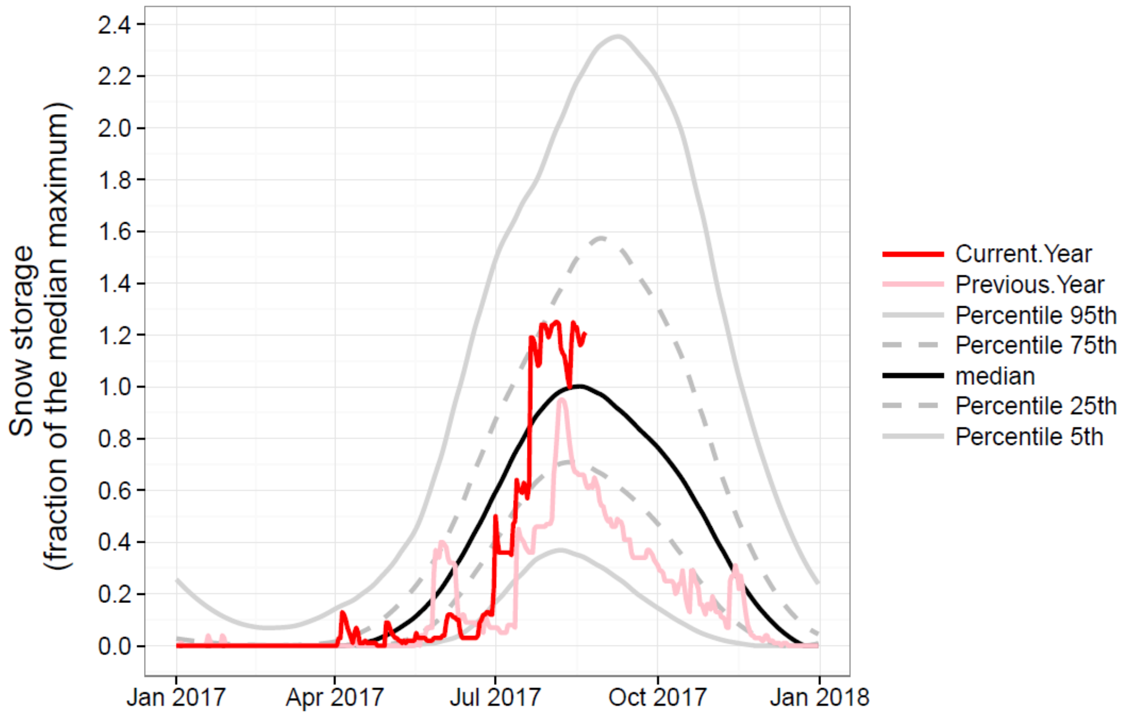

Figure 1. Example of the Lake Opuha Snow Storage Estimation System graph.

[3]R Core Team (2016). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienn a, Austria. URL https://www.R-project.org/.

The snow storage estimates are prepared from the daily temperature and rainfall data obtained from the MetService Fairlie climate station, and a digital elevation model of the catchment. Starting from April 1st of every year, when the snow storage is assumed to be zero, the temperature and precipitation across the catchment is estimated by extrapolating the climate station data, accounting for land height and the long-term average variation in precipitation. For those areas where the temperature is estimated to be below zero degrees Celcius, the precipitation is assumed to fall as snow. This snow is accumulated from day to day slowly building up the snow pack as the winter progresses. At the same time, in the areas where the temperature is above zero, snow is removed from the snow pack, at a rate linearly related to the temperature. This daily accounting of snow accumulation and snow melt continues throughout the winter until no snow remains. The whole process is repeated for over thirty years, with each day's total catchment snow storage related to the long term median for that day of the year. In this way the catchment's total snow storage is provided relative to the long-term median.

2.2 Forecast preparation

Lake Inflow forecasts are prepared by applying historic climate data to the future. For every year of historic data, one potential forecast is generated. Applying many historic years leads to a range of forecasts. This distribution of the forecasts enables estimation of the likelihood of different forecast outcomes.

Rainfall and temperature records from the MetService Fairlie climate station have been used to drive the snow storage model, and the forecasts.

To generate a forecast of lake inflows, an estimate of the current snow storage is first prepared using the snow storage model. The snow model is then run up to 6 months into the future thirty different times using the daily weather data from thirty different past years as the model input. Thirty years were modelled as this is the limit of the quality assured climate data that is available. The total catchment snowmelt and rainfall for every day of the thirty different forecasts is calculated. These daily totals are combined into month totals. For each month, these thirty different forecasts are compared to the range of possible forecast inflows. From this comparison, five different forecast types are prepared:

- Hi/Lo: the likelihood of the inflow being higher or lower than usual.
- Tercile: The likelihood of the inflow being in the top third of expected flows for that time of year, the likelihood of the inflows being in the middle third, and the likelihood of the inflows being in the lower third.
- Quartile: As for a tercile forecast except with respect to the four different quarters of the expected flows for the time of year.
- Quintile: as for a tercile forecast except with respect to the five different fifths of the expected flows for the time of year.
- Median: the middle forecast of the thirty forecasts.

Each of these forecast types are prepared for forecasts from 1 to 6 months into the future.

Table 1. Forecast types and description

Forecast Type	Number of classes	Class descriptions
Hi/Lo	2	More than usual, less than usual
Tercile	3	High, Ave., Low
Quartile	4	Very High, High, Low, Very Low
Quintile	5	Very High, High, Ave., Low, Very Low
Median	1	This is a single-value forecast

The different forecast types have been prepared to identify the highest level of detail that still provides some level of skill.

3 FORECAST SKILL

Summary

The probability forecasts show skill for August, September, October and December. The reason for the lack of skill for November is unknown. Tuning of model parameters (e.g. temperature lapse rates and melt rates) may offer an avenue to resolve this. The dominance of rainfall combined with the rapid melting of snow after a snow fall are considered the primary explanations for the generally low skill levels.

The single-value forecasts show skill for all months and lead times up to December, but the statistical significance of the skill is only reasonable (i.e. less than a 1 in 10 likelihood of occurring by chance) for September and December forecasts.

Details.

Forecast skill is a measure of how well the future is predicted. This is achieved through comparison of the forecast to what actually happens. If the forecast does well at predicting what happens then it is given a higher skill score.

3.1 Probability forecasts

Many measures exist for forecast skill. When forecasts are provided as probabilities of being within specific ranges, the Ranked Probability Score[4] is an appropriate skill measure. The Ranked Probability Score measures how well the observed range is predicted by the forecasted probabilities. A Ranked Probability Score of 0 indicates the forecast perfectly predicts the inflow range every time. A number equal to the number of forecasts being tested, indicates the forecast is always incorrect. A forecast that is not perfect may still be useful. The usefulness of the forecast may be determined by comparing the Ranked Probability Score of the forecast against the Ranked Probability Score of a default forecast.

For the purposes of Lake Inflows, a forecast is only useful if it is better at estimating the inflows than what the long term average would predict. For Lake Opuha the long-term average monthly inflows are displayed in Figure 2. These data are from the inflow estimates prepared by Environmental Consulting Services, based on a combination of the South and North Opuha stream flows. For an inflow forecast to have useful skill, it needs to do a better job at predicting the lake inflows than these long-term averages.

[4] Joliffe, I.T., Stephenson, D.B., 2012. Forecast Verification. A Practitioner's Guide in Atmospheric Science, 2nd ed. Wiley-Blackwell, Chichester, UK.

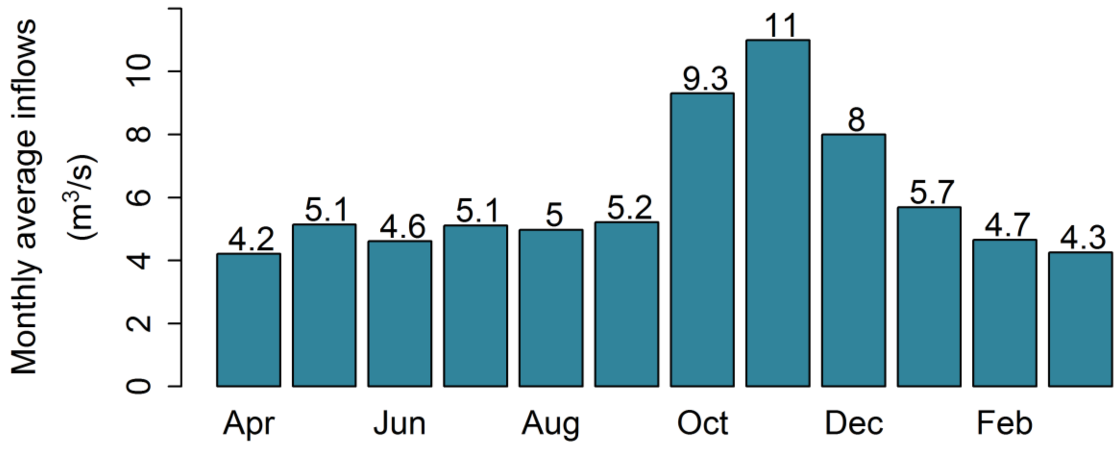

Figure 2. Long term average inflows to Lake Opuha.

The measure of the forecast skill, relative to the long-term average is the Ranked Probability Skill Score. For this measure, a value of 1 indicates the forecast is perfect, a measure of 0 indicates the forecast is no better than the long-term average. A negative score indicates the forecast is worse than the long term average. Full details of the calculation of the Ranked Probability Skill Score are provided in the appendix.

This Skill Score has been used to measure the skill of the Lake Opuha inflow forecasts.

Forecasts were prepared on the last day of the month from July to November for every year that climate data were available. The forecast procedure is described below:

1. Total monthly rainfall-plus-snow-melt was estimated for every month of every year.
2. For each month-type (e.g. all Augusts, all Septembers, etc.), the range of total-monthly-rainfall-plus-snowmelt was classified into 2,3,4 and 5 equal sized classes to match the different forecast types (see Table 1).

For each forecast day the following steps were taken:

3. Total catchment snow storage was estimated for the forecast day.
4. Thirty different possible future monthly-total-rainfall-plus-snow-melt series were prepared using the climate data from every year, except the year of the forecast.
5. The range of these thirty futures were classified into the categories established in (2) above.
6. The number of forecasts within each category, divided by the total forecasts were established. This is the probability forecast.

Finally all the different forecasts were put into time- series prior to testing the skill.

Time- series were generated for each lead time (from 1 to 6 months) and each forecast type (HiLo, Tercile, Quartile, Quintile).

The results of the Skill Score for all of these forecast time series are presented in the graphs in Figure 3.

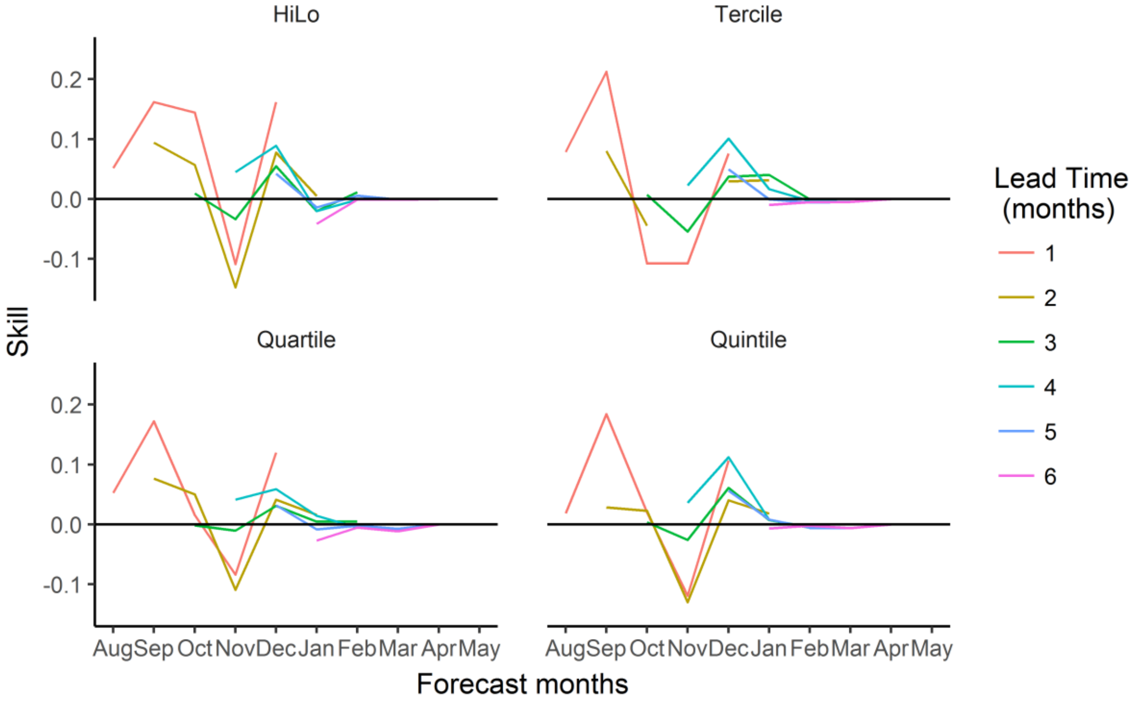

Figure 3. Graphs of skill scores for different forecast types and lead times. Skill scores below -0.1 are not shown.

Working by month, as the first forecasts were generated at the end of July, the forecasts for August are only ever at a one month lead time (red lines). For all forecast types, the forecasts show a slight improvement over using the long term average.

For September, one month (red) and two month (brown) lead time forecasts are available. For all forecast types, there is still more skill in the forecast than the long-term average, though the one month lead time forecasts (red lines) are always better than the two month lead time forecasts. The one month lead time forecasts of September are the forecasts with the most skill, but are still only 20 % better at forecasting the September inflows than using the long term averages.

For October the forecast skill is only better than the long term average for the one and two month lead time forecasts for the HiLo type, and for the two month lead time for the Quartile type. This means October inflows cannot be forecast with any skill from July.

For November, the only forecasts with any skill are the 4 month lead time forecasts, generated in July.

For December some skill (albeit small) returns for all lead times.

The overall poor performance of the forecasts is a reflection of the relatively low importance of melt from stored snow to the lake inflows relative to rainfall. Figure 4 shows the modelled portion of inflows that comes from melt of snow that has been stored from a previous month. Actual snow melt for any month is higher than this, but most of it is coming from the snow that falls during the same month that it melts, which is of no use for forecasting. Even for October, knowledge of the size of the snow pack in September can only help with forecasting of one quarter of the inflows. Note that these estimates are less than, and earlier than, what the long term inflows indicate (Figure 2). This suggests that the snow model is under-estimating snow accumulation, and/or the modelled melt rate is too high.

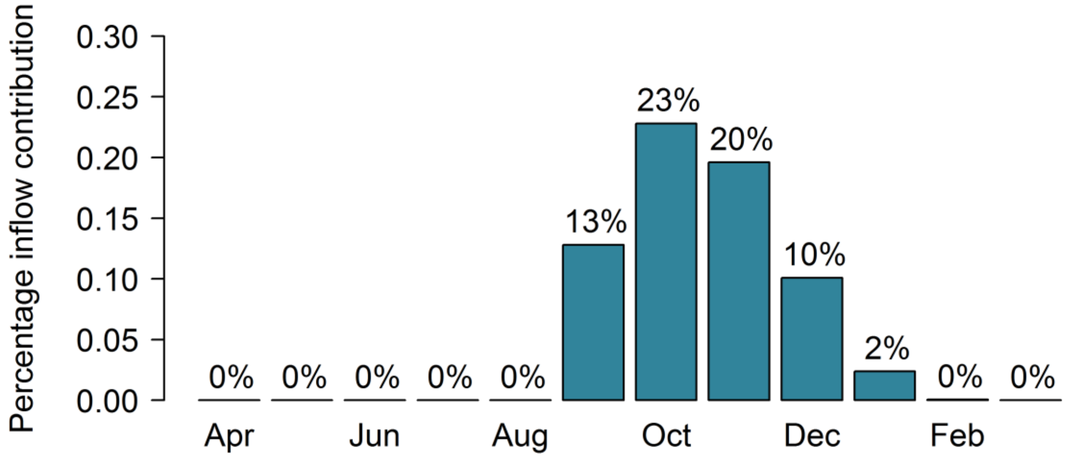

Figure 4. Proportion of inflows derived from melt of snow that has been stored from previous months.

The particularly poor performance of the forecasts for November indicate that the lack of consideration of the other components of the hydrology (e.g. soil moisture storage, groundwater storage, evapotranspiration) may be limiting the forecast. Increased sophistication of the model could be a consideration for lifting the performance of the October and November forecasts. Alternatively, the model (currently using a default set of parameters including lapse rates and melt rates) could be calibrated specifically to the Lake Opuha catchment.

Some preliminary investigation has been made into using different melt-rates at different times of the year (as may be considered likely to occur through processes like changes in solar radiation, snow patchiness, and snow pack temperature) but without significant improvement. The benefit of improving the November forecast skill would provide a valid reason for further snow model development.

3.2 Single value forecasts

In addition to the assessment of the skill of the probabilistic forecasts, the use of the median forecast has been assessed for skill. As the median is a single number its use is conceptually simpler and possibly more intuitive (albeit less informative). Kendall's tau[5] has been selected as a measure of the skill of the single-value forecasts. Kendall's tau statistic is a common measure of how well the ranking of a series of numbers matches the ranking of a separate series. Kendall's tau does not make any assumptions about the underlying distribution of the forecasts or observations, making it robust for hydrological data, which commonly does not have a clearly defined distribution. Kendall's tau returns a value from -1 to 1, where a value of 1 indicates the ranking of the forecasts exactly matches the ranking of the observations. A value of 0 indicates there is no correlation between the rankings. A value of -1 indicates the ranking is completely opposite to the inflows. It is possible that by pure chance a random set of numbers could have the same ranking as the inflows. Kendall's tau enables the likelihood of the returned value occurring by chance (the p value). The p value gives an indication of the statistical significance of the skill.

A plot of Kendall's tau statistic for the single value forecasts is shown in Figure 5. This indicates that for all months, except January, the ranking of the forecasts, to some extent, match the ranking of the observed inflows. The forecasts for September and December show the most skill. While positive skill is observed, this could be purely by chance. Figure 6 displays the likelihood of the Kendall's tau values occurring by chance. This graph indicates that the skill levels obtained for the October and November forecasts could occur purely by chance once in every three times (for October), and once every two times for November. This means that the skill of the October and November single-value forecasts are

[5] Kendall, M. (1938). "A New Measure of Rank Correlation". Biometrika. 30 (1–2): 81–89.

not statistically significant, and that they are of little value. This supports the findings from the probabilistic forecasts.

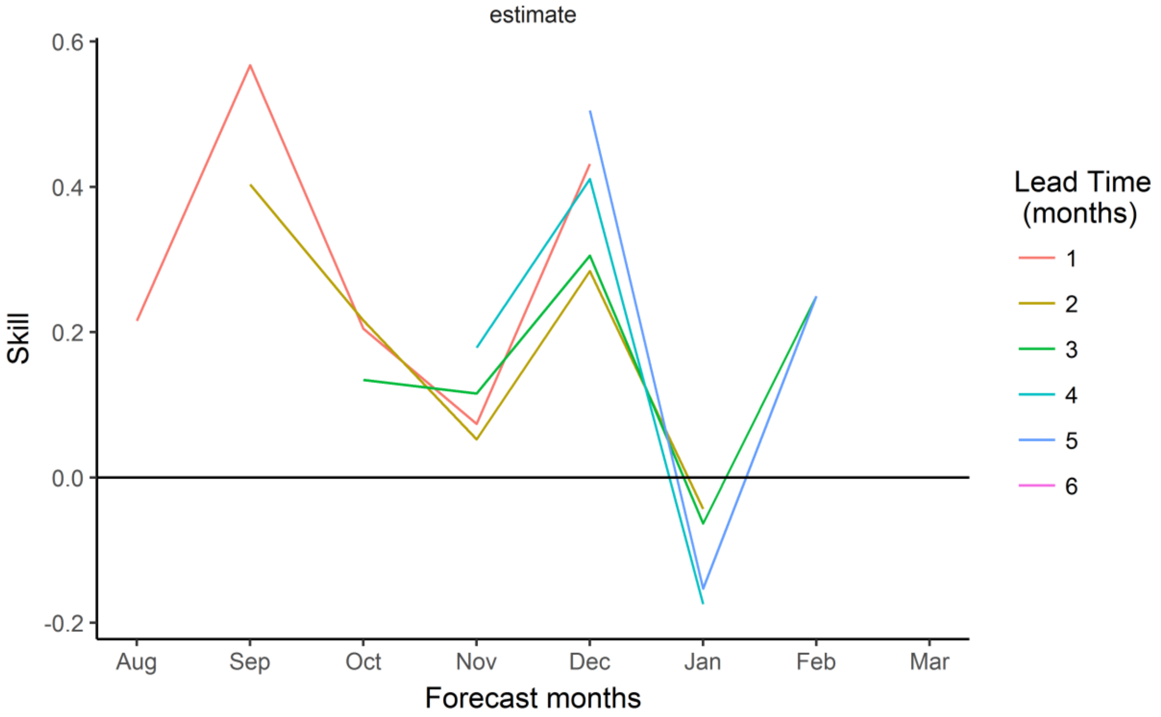

Figure 5. Skill of the single-value forecasts as measured by Kendall's tau statistic. A value greater than 0 indicates the ranking of the forecasts matches the ranking of the observed inflows to some degree.

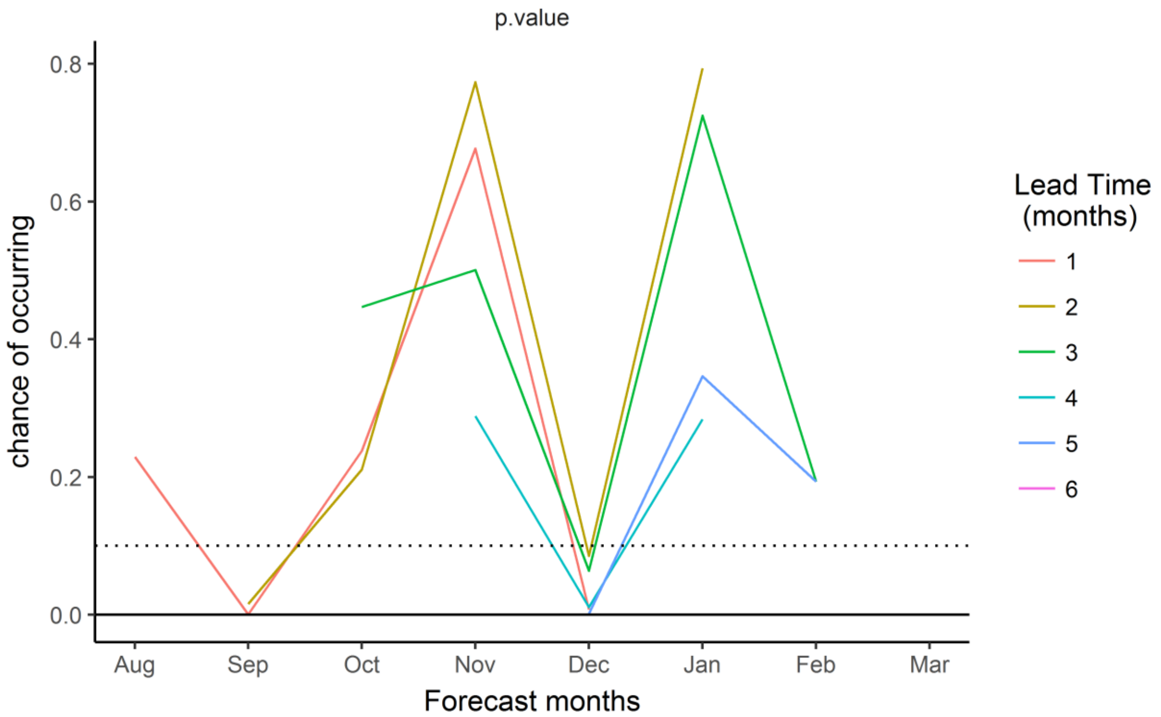

Figure 6. Likelihood of the Kendall tau values depicted in Figure 5 occurring by chance. The horizontal dotted line indicates the likelihood of 1 chance in 10.

4 SNOW STORAGE QUANTITY AS A WATER VOLUME

Summary

The long term median snow storage at the height of the winter season is 22 Mm^3 or 1/3 of the volume of Lake Opuha. This is equivalent to 40 days at the annual average inflow of 6 m^3/s.

Details

Currently the Lake Opuha catchment snow storage system provides estimates relative to the long term median. This measure has been used because it is the relative size of the snowpack that is important for anticipating the impact of future melt.

Establishing an absolute measure of the snow pack in terms of water amount has the advantage that the values can be put into perspective of inflow quantities and lake storage.

Quantifying the snow storage requires determining the correct scaling factor of the Fairlie rainfall (the snow model's data source). The model currently uses a scale determined from the 1951-1980 mean annual rainfall map of New Zealand[6]. This map was prepared using expert judgement from long term rainfall observations at predominantly low elevation sites. This map shows the Lake Opuha Catchment to have a mean annual precipitation 1.5 times greater than the Fairlie weather station, i.e. 1125 mm (Fairlie weather station has an annual average of 750 mm). With the new precipitation gauges at Dobson and Fox Peak, this map will be able to be revised. Until that happens, this rainfall map is the best estimate of how precipitation varies across the catchment. The magnitude of the precipitation across the catchment may be checked by balancing the water budget, so that the Lake Inflows equal rainfall less evapotranspiration. At a long-term annual level, changes in soil moisture, groundwater and snow storage may be considered to equal 0. Estimates of long-term potential evapotranspiration are available from the Land Environments of New Zealand (LENZ)[7] data available from the Landcare LRIS Portal[8]. LENZ data include long term average monthly ratio between rainfall and PET, and the long term average difference between potential evapotranspiration and actual evapotranspiration (the soil moisture deficit).

$$Rain = Inflows + PET - Deficit$$

Average annual inflows are 6 m^3/s, which is the equivalent of 500 mm depth over the whole catchment.

The average annual potential evapotranspiration over the catchment is 479 mm

The average annual soil moisture deficit is 82 mm

So based on the LENZ estimates of PET and soil moisture deficit, the catchment annual average rainfall should be 897 mm.

This is 0.8 of the rainfall estimate by the rainfall map, so the snow storage estimates need to be multiplied by 0.8 to scale them to the water balanced estimates.

Using this scale,the long term median snow storage at the height of the winter season is 21.7 Mm^3 or 0.33 lake volumes (where lake volume is taken to be 65.5 Mm^3). This is equivalent to 41 days at 6 m^3/s, and is a close match to the inflows from October-December that are in excess of the average annual inflows.

A graph of the snow storage with a scale in water volume as millions of cubic metres and as lake volumes is shown below. This indicates that as of the end of August there is the equivalent of 30% of the lake volume stored in the snow of the catchment.

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[6] NZMS, 1985. New Zealand Annual Rainfall: Normals 1951-1980. New Zealand Meteorological Service Miscellaneous Publication No 175, Part 6, Annual rainfall map. New Zealand Meteorological Service. Wellington.

[7] Leathwick, J., Morgan, F., Wilson, G., Rutledge, D., McLeod, M., Johnstone, K., 2002. Land Environments of New Zealand: A Technical Guide. Ministry for the Environment.

[8] https://lris.scinfo.org.nz/

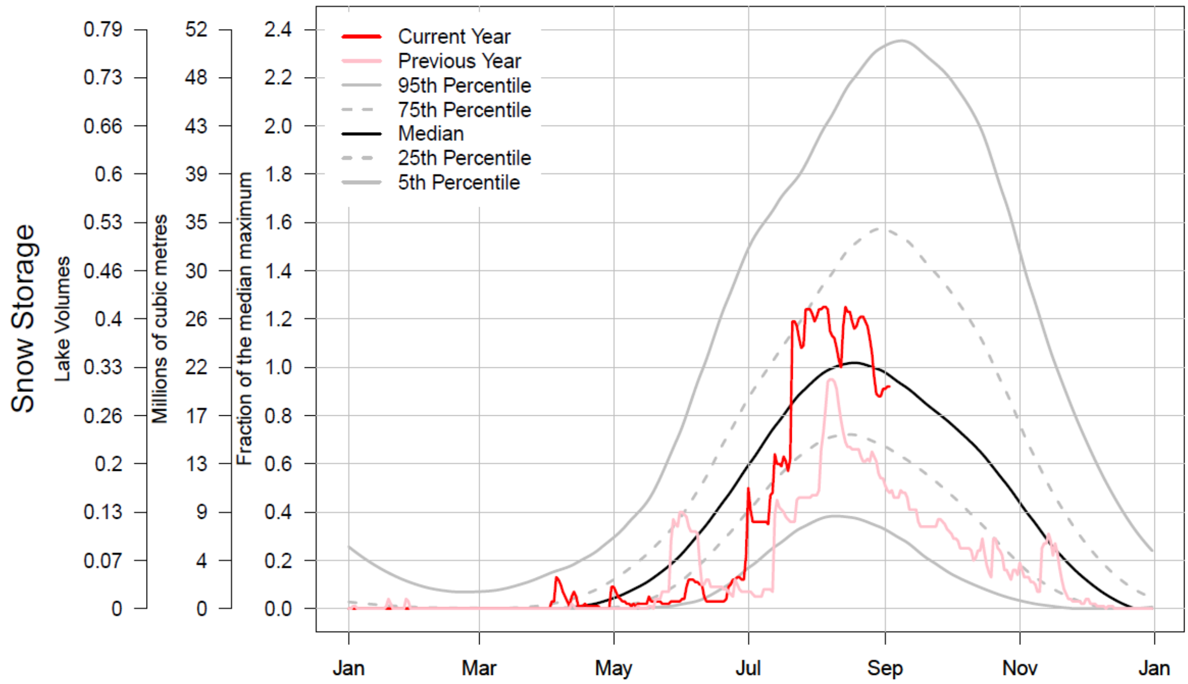

Figure 7. Estimation of snow storage in the Lake Opuha Catchment measured with respect to total lake volumes, millions of cubic metres, and relative to the seasonal maximum of the long term median

5 SNOW STORAGE OPTIMISATION

Summary

Modelling the entire catchment provides the best 1 and 2 month lead-time forecasts, but modelling just the catchment above 1800 m provides better 3-5 month lead-time forecasts of December and January inflows.

Details

Consideration of a subset of the Lake Opuha catchment for snow storage may enable improved inflow forecasting when the forecasts are based on a relationship between snow storage and later inflows. This is based on the idea that lower elevations of the catchment (e.g. across Ashwick Flat) are unlikely to store the snow for very long after a snowfall occurs. During the development of the forecasts, the approach to generating the inflow estimates has changed. The forecasts are now not based on statistical relationships between snow storage and later inflows, but on repeated model runs using historic data. The model runs estimate the total catchment rainfall and total catchment snow melt. Using a subset (based on elevation) of the catchment will reduce these rainfall and snowmelt totals and lead to forecast probabilities biased to the snowmelt component of the inflows, and not a true representation of the rainfall-dominated inflows. Nevertheless, different lower elevation limits were tested to see if they improved the inflow forecast skill. Subsets of the catchment based on minimum elevations of 1600 m and 1800 m were tested.

Below are the skill score plots for the > 1600 m catchment (Figure 8) and the > 1800 m catchment (Figure 9). These plots may be compared to Figure 3, which showed the skill scores when the entire catchment was considered. This test indicates the skill of the forecasts are lower for the limited catchments for the short lead time forecasts, but the 3 to 5 month lead time forecasts for December and January improve.

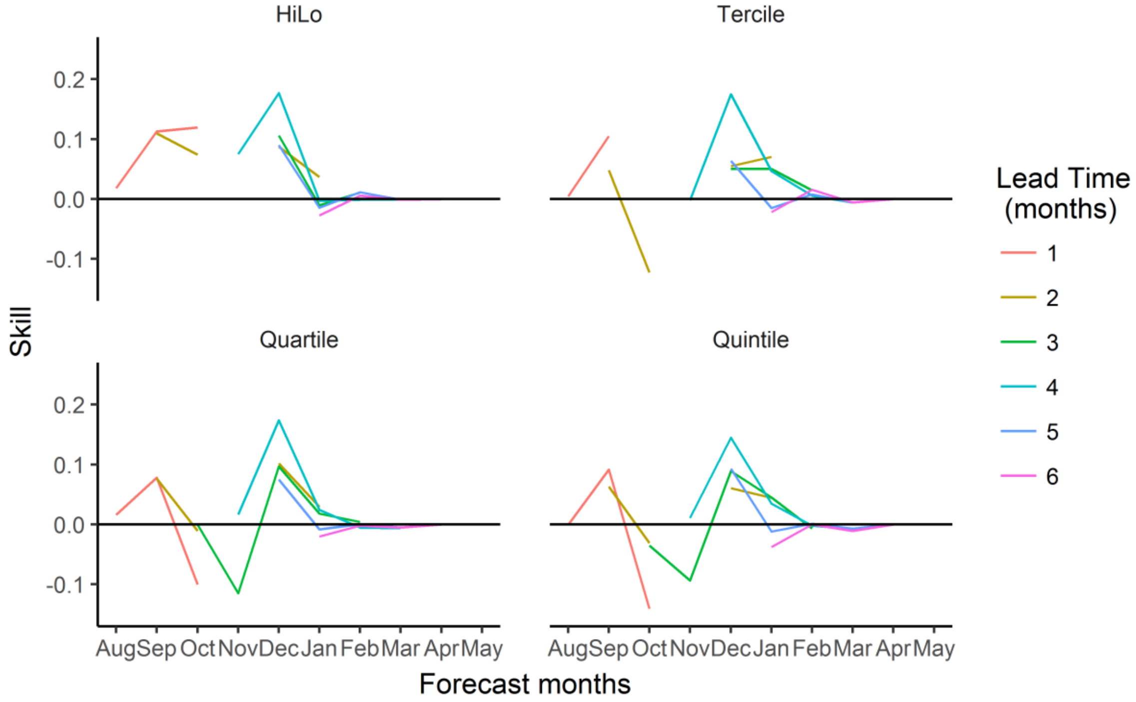

Figure 8. Forecast skill score plots when only the catchment above 1600 m is considered. Skill scores below -0.1 are not shown.

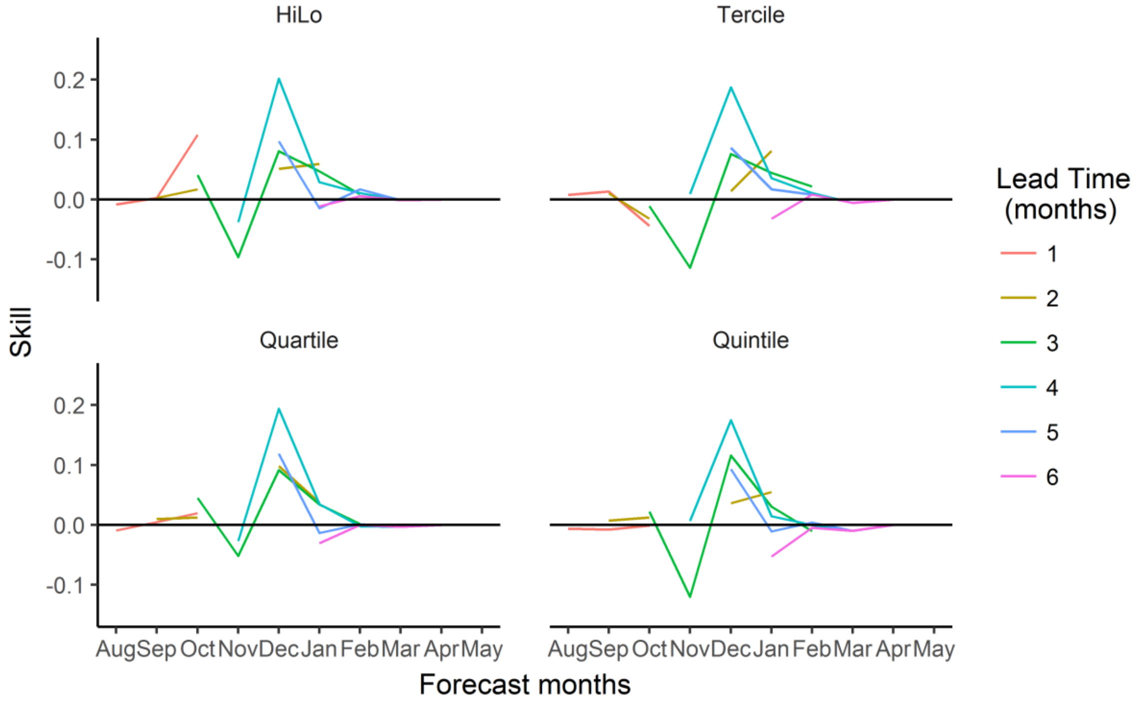

Figure 9. Forecast skill score plots when only the catchment above 1800 m is considered. Skill scores below -0.1 are not shown.

6 2017 FORECASTS

Summary

The inflows are not forecast to be biased high or low compared to the long term average for the next two months. December inflows are forecast to have a slightly greater chance of being in in the lowest 20 percentile. This indicates that the snow distribution is at lower elevations than on average.

Details

Inflow forecasts for 2017 are presented here. Following the results of the skill score analysis, only the lead times and forecast types that have demonstrated skill greater than the long term average are shown. Forecasts were generated based on the August 27th snow storage estimates (Table 2), and for comparison, the forecast based on the July 31st snow storage estimates are provided in Table 3. These forecasts are based on the snow model that uses the entire catchment.

The forecasts provide the chance (in percentages) that the resulting inflow band occurs. Generally the forecasts indicate that each of the inflow bands have an approximately equal chance of occurring. This is in line with the snow storage being near the long term median. In a low snow year, the forecasts would show increased chance of the inflow being in the lower bands. These forecasts formalise the subjective assessment that people make when they consider the snow storage in the catchment, but with the benefit of thirty years of experience, and with a correct understanding of the contribution the snow melt makes to the inflows.

Potential exists for these forecasts to be presented in different ways. While the forecasts are provided here as tables of numbers, they could equally be presented in a bar or pie graph format. If the forecasts are to be operationalised, then the most intuitive way to communicate the values will need to be identified.

Table 2. Inflow forecasts from 27th August 2017. NS indicates no-skill

Forecast Type	Very Low	Low	Ave.	High	Very High
September					
Quintiles	19%	23%	16%	29%	13%
Quartiles	23%	29%		26%	23%
Terciles		32%	32%	35%	
Hi/Lo		52%		48%	
November					
Quintiles	NS	NS	NS	NS	NS
Quartiles	NS	NS		NS	NS
Terciles		NS	NS	NS	
Hi/Lo		NS		NS	

Forecast Type	Very Low	Low	Ave.	High	Very High
October					
Quintiles	13%	26%	23%	13%	26%
Quartiles	16%	32%		19%	32%
Terciles		NS	NS	NS	
Hi/Lo		48%		52%	
December					
Quintiles	29%	19%	19%	16%	16%
Quartiles	29%	26%		23%	23%
Terciles		42%	26%	32%	
Hi/Lo		55%		45%	

Table 3. Inflow forecasts from 31st July 2017. NS indicates no-skill.

Forecast Type	Very Low	Low	Ave.	High	Very High
September					
Quintiles	6%	19%	19%	26%	29%
Quartiles	16%	32%		16%	42%
Terciles		19%	26%	55%	
Hi/Lo		42%		58%	
November					
Quintiles					
Quartiles	29%	23%		23%	26%
Terciles		39%	26%	35%	
Hi/Lo		52%		48%	

Forecast Type	Very Low	Low	Ave.	High	Very High
October					
Quintiles	NS	NS	NS	NS	NS
Quartiles	NS	NS		NS	NS
Terciles		NS	NS	NS	
Hi/Lo		39		61	
December					
Quintiles	29%	19%	19%	16%	16%
Quartiles	29%	32%		16%	23%
Terciles		35%	32%	32%	
Hi/Lo		61%		39%	

Appendix A: Ranked Probability Skill Score

This Appendix is taken from section 8.4.2 of Forecast Verification, A Practitioner's Guide in Atmospheric Science, by Ian Jolliffe, and David Stephenson, Wiley-Blackwell, 2012.

In the following, K denotes the number of categories, and C_k denotes the climatological probability that the observed outcome is in category k.

For example, when simply forecasting high inflows or low inflows, there are just two categories, so $K = 2$. The long term probability of the inflows for a particular month being high is half, so C_1=0.5. Likewise, the long-term probability of the infows for a particular month being low is also half, so C_2=0.5.

For a set of n forecast-observation pairs, $\hat{p}_{t,k}$ is the probability assigned by the t^{th} forecast to the k^{th} category. Further, $y_{t,k}$ = 1 if the ith observation is in category k, and $y_{t,k}$=0 otherwise. $\hat{P}_{t,k}$ and $Y_{t,k}$ denote the k^{th} component of the t^{th} cumulative forecast and observation series, and C_k the k^{th} category of the cumulative climate distribution; i.e.

$$\hat{P}_{t,k} = \sum_{l=1}^{k} \hat{P}_{t,l}$$

$$Y_{t,k} = \sum_{l=1}^{k} Y_{t,l}$$

$$C_k = \sum_{l=1}^{k} C_l$$

From these equations the Ranked Probability Score (RPS) of the forecast is given by:

$$RPS = \frac{1}{n}\sum_{t=1}^{n}\sum_{k=1}^{k}\left(\hat{P}_{t,k} - Y_{t,k}\right)^2$$

Similarly the Ranked Probability Score (RPS) of the long term probabilities, is given by:

$$RPS_{long\ term} = \frac{1}{n}\sum_{t=1}^{n}\sum_{k=1}^{k}\left(C_k - Y_{t,k}\right)^2$$

Lastly, the Ranked Probability Skill Score is simply one minus the ratio of the two Ranked Probability Scores.

$$RPSS = 1 - \frac{RPS}{RPS_{long\ term}}$$