APPENDIX W-2

PROJECTED CLIMATE CHANGE EFFECTS ON THE WATER BALANCE

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Memorandum

To: Kyle Stanfield, New Gold Inc.
cc: David Simms, AMEC
From: Ben Harding, AMEC
Subject: Rainy River Project, Projected Climate Change Effects on the Water Balance
Date: October 11, 2013

This memorandum provides estimates of the effect of projected future climate on the water balance at the Rainy River Project (RRP), and describes the approach used to make those estimates. The RRP is being developed by Rainy River Resources Ltd. It is located in the Township of Chapple, District of Rainy River, in northwestern Ontario, approximately 65 km northwest of Fort Frances, and 420 km west of Thunder Bay, at an elevation of 375 m.

Current estimates of precipitation and open-water evaporation at the RRP site are 695 mm and 600 mm, respectively. Projections were made for thirty-year average values representing the estimated future conditions in 2020, 2050 and 2080.

Projected Changes in the Future Water Balance

Table 1 provides estimates of the net effect of climate change on the annual water balance at the site. Estimates are provided for three future periods and for the 5th, 25th, 50th, 75th and 95th non-exceedance percentile values across the ensemble of General Circulation Model (GCM) projections of future climate. Estimates from Table 1 for the desired non-exceedance percentile and future time frame should be added to the baseline water balance.

Table 1: Adjustments to the Annual Net Water Balance (mm)
(Values rounded to two significant figures)

Non-exceedance Percentile	2020	2050	2080
5	55	48	20
25	83	78	69
50	100	110	100
75	120	130	140
95	150	170	190

Adjustments from Table 1 can also be used to estimate the effect of climate change on the long-term water balance in the soil on vegetated areas. These adjustments do not reflect the effect of heavy precipitation on runoff.

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Interpretation of Uncertainty

Table 1 provides values at the 5th, 25th, 50th, 75th and 95th non-exceedance percentile across the ensemble of projections. These reflect the differences in projections of future climate conditions across the climate models. There is considerable scientific disagreement about how to apply climate projections to impact assessment. Some research suggests that the range of estimates of impact based on a large ensemble of projections is a minimum bound and is practically irreducible, at least in the foreseeable future (Stainforth et al., 2007; Wilby, 2010). Other research suggests that it may be possible to develop probabilistic estimates of impacts (Tebaldi and Knutti, 2007), and a skillful ensemble mean (Gleckler et al., 2008).

The recommended approach, which is the most conservative handling of uncertainty, is to use the extremes in the distribution of results to represent minimum bounds of possible future conditions. In this approach, the 5th and 95th percentile values would be used to characterize the lower and upper bounds of the possible changes in the annual water balance. Even these bounds may not capture the true future water balance and the probability that future values will fall outside those bounds is not known and is not knowable. As unsatisfying as this interpretation may be, it is the approach best supported by the current state of scientific knowledge.

The less conservative approaches would be to use the ensemble median as the most likely future condition, or to interpret the frequency distribution as an indication of the risk of exceedance.

Approach

<u>Current Climate</u>

A daily meteorological climatology that includes precipitation, maximum temperature, minimum temperature and wind speed for the period from 1949 through 2005, developed as described in Maurer et al. (2002), but extended through 2007, formed the historical climatology and forcing dataset used in this study (Wood, 2010). The data are aligned spatially to match the NOAA/NASA Land Data Assimilation System (LDAS; Mitchell et al., 2004) grid, which has a spatial resolution of 1/8th degree latitude by longitude and covers a domain from 25N to 53N and 67W to 125W, which includes the continental United States as well as part of Canada and Mexico. A four-cell subset of the LDAS grid overlaying the RRP site was used in this work. The relationship to the LDAS grid cells and the RRP site is shown in Figure 1

Value of climate variables at the RRP site were estimated by weighting the Maurer values for the four selected LDAS grid cells proportional to the inverse of distance from the site.

<u>Climate Projections</u>

This project used downscaled projections obtained from the bias-corrected and spatially downscaled archive developed by Maurer (2007) and Reclamation (2013) according to the methods described in Maurer et al. (2009), Maurer, et al. (2002) and by Reclamation (2013).

The projections were provided through the World Climate Research Programme's Coupled Model Intercomparison Project Phase 3 (CMIP3) and Phase 5 (CMIP5) multi-model dataset (WCRP, 2013).

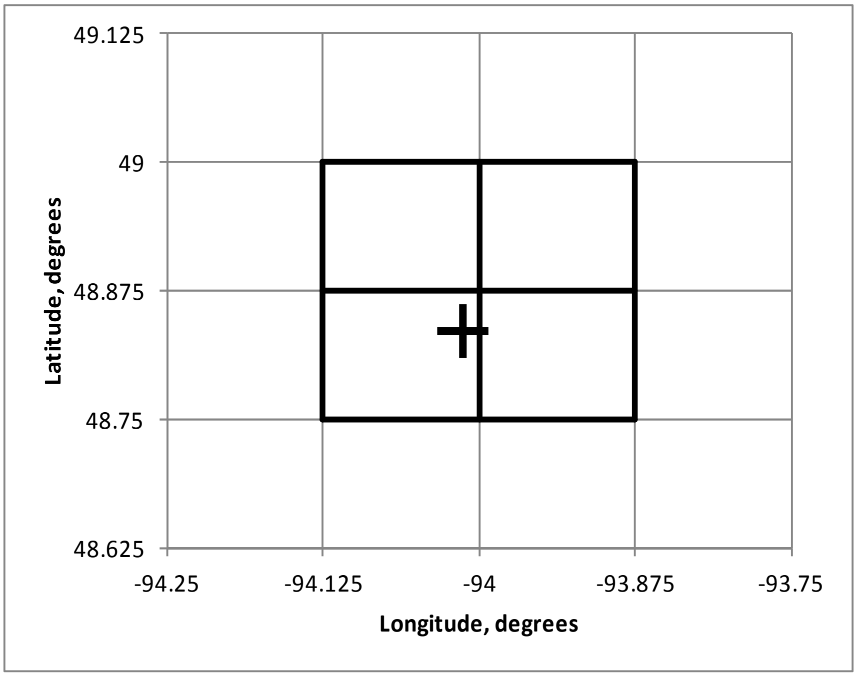

Figure 1: LDAS Grid and RRP Site
(Site designated by cross, cell subset in bold outline)

Model runs that are part of the Coupled Model Inter-comparison Project, Phase 3 (CMIP3) (PCMDI, 2013), collectively referred to as the *CMIP3 ensemble,* were used as the basis for the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4; IPCC, 2007). The CMIP3 ensemble consists of 112 runs of 16 GCMs (climate models, referred to as General Circulation Models or Global Climate Models). The CMIP5 ensemble will serve as the basis for the IPCC Fifth Assessment Report to be published beginning in the fall of 2013. (There is no fourth phase to CMIP; phase numbering was advanced from three to five to be consistent with the numbering of the Assessment Reports.) The CMIP5 ensemble consists of 234 runs of 24 GCMs.

The WCRP archive contains projections of monthly temperature and precipitation, aligned spatially with the LDAS grid, with each projection consisting of an overlap period of 1950 through 1999 and a projection period of 2000 through 2099. The CMIP3 archive contains projections of monthly precipitation and mean temperature. All CMIP5 runs include projections of monthly precipitation and monthly mean temperature; some also include projections of monthly average daily minimum and daily maximum temperature. Only projections of mean temperature were used in this work.

The monthly climate datasets were produced using the statistical bias-correction and spatial disaggregation (BCSD) method described in Wood et al., 2002 and 2004. The method was first implemented for downscaling general circulation model seasonal climate predictions to support hydrologic forecasting (Wood et al., 2002; Wood et al., 2005; Wood and Lettenmaier, 2006) and adapted for downscaling future climate scenario model output (Wood, 2004; also Christensen et al., 2004; Van Rheenen et al., 2004; Payne et al., 2004). The BCSD method has since been employed in a number of more recent climate change impact analyses, in regions such as the western US (Christensen and Lettenmaier, 2007; Barnett et al., 2008; Maurer, 2007), the continental US (Maurer et al, 2002; Maurer and Hidalgo, 2008), and central America (Maurer et al., 2009) among other locations.

Figures 2 and 3 show the evolution of 30-year mean values of precipitation and temperature at the RRP site for the combined CMIP3 and CMIP5 ensemble (346 model runs).

<u>Estimates of Changes in Precipitation and Temperature</u>

The projected change climate in conditions is determined for each climate projection by comparing the climate condition during the overlap period from the climate condition at some future point in time, and applying that projected change to historical conditions. The overlap period is the period of time where the model simulation overlaps the observed climate; in this work the overlap period is 1950 through 1999. The climate condition during the overlap period is represented as the average for the period 1950 - 1999 and the climate condition at the future point in time is represented as a 30-year average centered on that point in time. The projected conditions were estimated for three future time periods, 2020, 2050, and 2080. The averaging periods for those time frames were, respectively, 2005 through 2024, 2035 through 2064 and 2065 through 2094.

Projections of change in precipitation are a direct input to the water balance. Estimates of projected future temperature were required in order to calculate estimates of change in future evaporation. Future precipitation and temperature were estimated by perturbing the current conditions by the projected change, a method referred to as a “delta” approach (Miller, 2003). The method for adjusting climate variables is illustrated in Figure 4.

In adjusting precipitation the change is in the form of a ratio as shown in Equation 1.

$$P_p = P_c \frac{P_{sf}}{P_{so}} \quad (1)$$

Where: P_{sf} is the simulated future precipitation, P_{so} is the simulated overlap precipitation, P_c is the current observed precipitation and P_p is the projected future precipitation. In adjusting temperature, the “delta” was in the form of an offset, as shown in Equation 2.

$$T_p = T_c + \left(T_{sf} - T_{so}\right) \quad (2)$$

Where: T_{sf} is the simulated future temperature, T_{so} is the simulated overlap temperature, T_c is the current observed temperature and T_p is the projected future temperature.

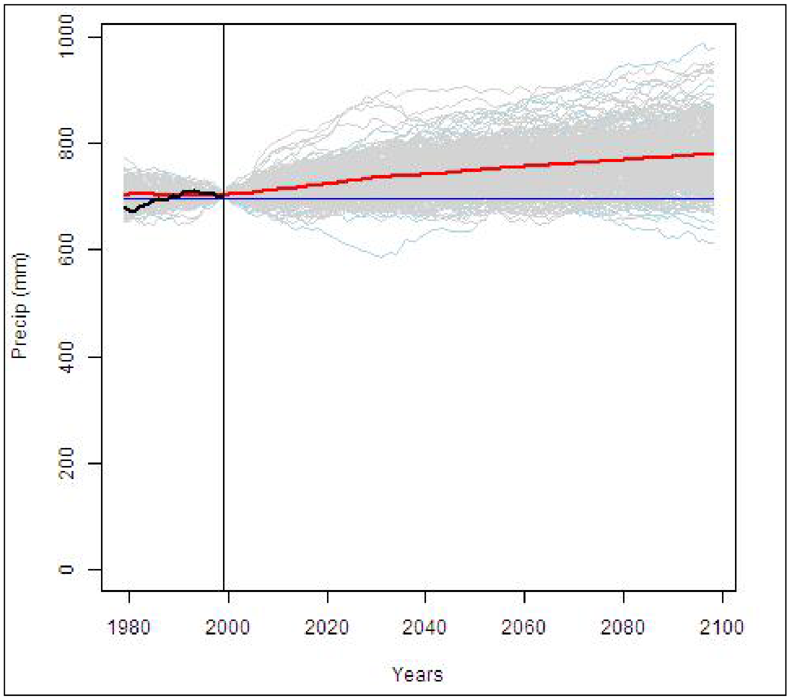

Figure 2: Projected Precipitation at the RRP Site

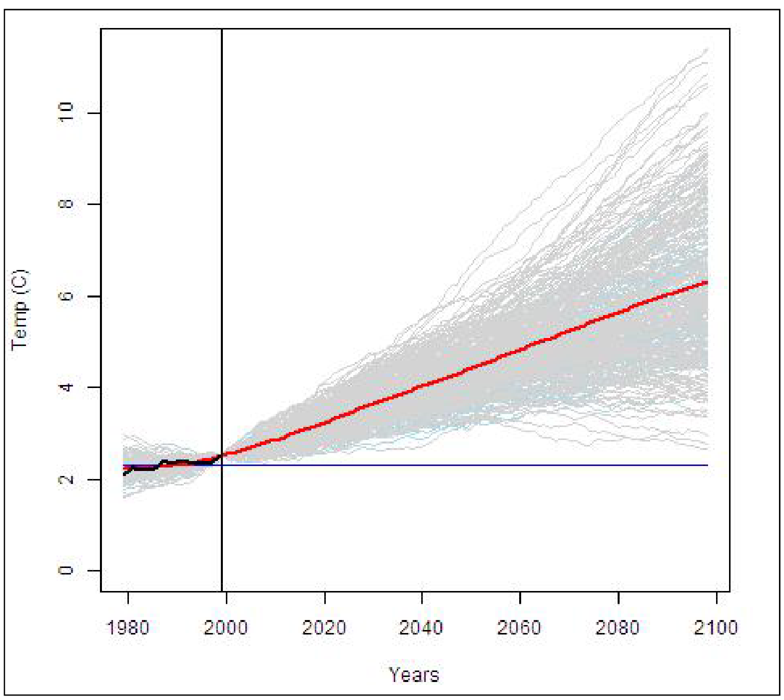

Figure 3: Projected Temperature at the RRP Site
(Historical mean, black; Projected mean, red)

In this application the delta approach is preferred over using climate projections directly because the delta method reduces the bias inherent in climate simulations.

The model of evaporation also exhibits inherent bias, so estimates of change in projected evaporation were calculated according to an equation of the form of Equation 1.

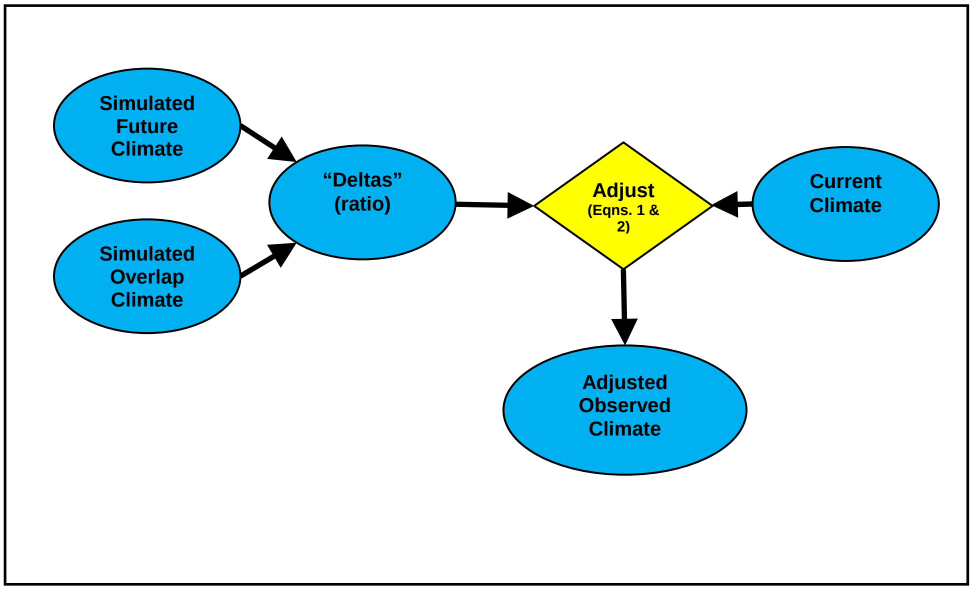

Figure 4: Development of Adjusted Observed Climate using the Delta Method

<u>Estimation of Changes in Evaporation</u>

Estimates of evaporation were made using the Penman-Monteith equation (FAO-56, Allen et al., 1998). The Penman-Monteith Equation is a physically oriented model of reference evapotranspiration that has been applied successfully around the world. Typically, the primary inputs to the Penman-Monteith equation are measurements or estimates of incoming shortwave solar radiation, air temperature, air humidity and wind speed. Estimates of reference evapotranspiration using the Penman-Monteith equation can be made on an hourly, daily or monthly basis. When modeling open-water evaporation, the reference evapotranspiration (also thought of, conceptually, as potential evapotranspiration) is converted into an estimate of evaporation by the use of an open-water coefficient, which is 1.05 (Allen, et al.,1998)

Projections of future climate provide only estimates of future changes in mean temperature, so missing input data were estimated as follows (Allen et al., 1998).

Maximum and minimum temperature. Current monthly average daily maximum and daily minimum temperatures were perturbed equally by the projected change in mean temperature, according to Equation 2.

Incoming shortwave radiation. Radiation was estimated based on perturbed maximum and minimum temperature using the Hargreaves Equation (Allen, et al., 1998).

Air humidity. Air humidity was represented by the dew point temperature. Dew point temperature was estimated using the value of daily minimum temperature.

Wind speed. Wind speed was represented by the current monthly mean wind speed.

Correction of air temperature and dew point temperature for the effect of aridity is recommended by Allen et al. (1998) in cases where evaporation exceeds precipitation by a factor of two or more. Accordingly, no correction was required for this work. (Allen, et al., 1998).

Change in the rate of evaporation was estimated for a pond of approximately 2 m in depth located on a waste storage facility at the site. The Penman-Monteith equation was run for each month of the year based on the average projected climate conditions for that month. Averages were calculated over the overlap period or over the 30-year period representing a future time frame. In calculating incident solar radiation planetary parameters were assumed to be those on the 15th of the month. An open-water coefficient of 1.05 was used to adjust the estimate of reference (potential) evapotranspiration resulting from the Penman-Monteith equation to an estimate of open-water evaporation (Allen, et al., 1998).

Uncertainty in Estimates of Projected Conditions

Uncertainty reflects imperfection in our state of knowledge, as distinguished from variability, which is the effect of random processes. In practice, such a distinction is not clear cut, as, for example, the variability in atmospheric processes leads to considerable uncertainty about tomorrow's weather. Nevertheless, it is important to respect the distinction, because while variability can be addressed in quantitative ways, uncertainty must be addressed, at least in part, by subjective judgment (Vick, 2002). Accordingly, deciding how to use the results of this work in the face of uncertainty will be a policy decision. Some background on the sources of uncertainty and suggestions on how to consider the results herein are provided in the following paragraphs.

Barsugli, et al. (2009) identified the following sources of uncertainty in projections of future climate conditions:

Climate Drivers - The anthropogenic component of climate drivers is greenhouse gas emissions which are formally quantified in emission scenarios (CMIP3) or representative concentration pathways (CMIP5). These scenarios in turn depend on projections of future socio-economic, demographic and technical factors.

Climate Sensitivity - This is represented by the climate models themselves. The imperfections in climate models arise from coarse resolution, limitations in simulation of feedback mechanisms, limited knowledge of initial conditions and a number of other factors.

Downscaling - This is required because of the coarse resolution of climate models and the local nature of impact assessments. All downscaling techniques introduce uncertainty.

Further uncertainty arises for estimates of conditions at particular points in time due to “unforced variability”, which can be seen in the temporal variability of the individual traces in Figures 2 and 3 (Harding, et al., 2012).

In addition, there is uncertainty in the models used to assess impact, in this case the model of evaporation. For example, we have assumed, because we don’t have any better information, that wind speeds will not change. This is unlikely to be true, but we are not aware of scientific evidence to estimate future changes in wind speed in this region of the RRP.

Wilby and Harris (2006) found that the greatest uncertainty in studies of climate impact on hydrology arose from the climate models themselves, followed, in order, by the downscaling method, the hydrology model structure, hydrology model parameters (i.e. the calibration of the model) and finally by the uncertainty in future emissions scenarios.

Uncertainty in climate drivers and climate sensitivity can be represented by using a large number (an ensemble) of climate projections, as was done in this work. However, the readily available projections of climate conditions are derived using one downscaling technique, so the uncertainty inherent in downscaling is not represented in the projection ensemble. This uncertainty has not yet been quantified in the scientific literature.

The results presented herein represent one estimate of the range of future extreme precipitation intensity. That range is informed by the range of future projections of monthly average climate conditions, which themselves reflect the range of emissions scenarios and the different degrees of climate sensitivity among the GCMs. However, it is exceedingly important to recognize that an ensemble of projections, such as the one used in this study, may not capture the full range of uncertainty. That is, there is some unknown and unknowable probability that the actual future conditions are not contained in the range of projections in any given ensemble. Further, as noted above, there is additional uncertainty inherent in the downscaling technique and the statistical model that are not reflected in the currently available ensembles.

Accordingly, the results of this work should be used in combination with all relevant sources of information using careful professional judgment.

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