

Chill Portions and yield using actual data

Katja Schiffrers^a, Cory Whitney^a, Eduardo Fernandez^a and Eike Luedeling^a

^aINRES-Horticultural Sciences, University of Bonn, Auf dem Huelgel 6, 53121 Bonn, Germany

Data is often limited for assessing the relationship between temperatures and yield. Here we show how, despite this lack of data, we may still be able to make assessments and produce useful projections for farmers and decision makers. With the right tools this data limitation does not need to hinder our abilities to assess the relationships between temperature and yield. For coarse assessments a lot of data may not be necessary. We use the `pasitR` package (Schiffrers et al., 2018) in the R programming language (R Core Team, 2019) to illustrate methods whereby we can embrace the inherent uncertainty in such assessments to overcome the need for preciseness. We show a potential method for dealing with important but also necessarily uncertain relationships in model forecasts.

Yield and chill data

We offer an example of assessing yield given chill for sweet cherries (*Prunus avium* L.) ‘Lapins’ and ‘Brooks’ varieties. We applied procedures from the `pasitR` library for estimating yield as a function of chill accumulation (Schiffrers et al., 2018). The data was provided by the experimental orchard of the School of Agronomy at the Pontificia Universidad Catolica de Valparaiso (Table 1). We used weather data obtained from a local weather station (Table 2).

We used the `tempResponse_daily_list` in the `chillR` package (Luedeling, 2019) to compute the chill accumulation for each season. We defined the chilling season as the period between 1st of May and 31st of August (Table 3).

We used the `chillscatter` function to create a scatter plot of Chill Portions and yield. We calculated the associated estimated densities with loess smooth linear fits density curves using the `scatter.hist` function in the `plyr` package (Wickham, 2019).

We used `chillkernel` to perform a two-dimensional kernel density estimation for yield and chill using the `kde2d` function in the `MASS` package (Ripley, 2019). The density function restricts the shape of the kernel to a bivariate normal kernel, so this looks slightly different compared to the scatter plot estimates above.

`chillkernel` shows a density surface plot of Chill Portions (x) and yield (y). The legend shows the value for the estimated density (z). The plot is made with the `filled.contour` function of the `graphics` package (R Core Team, 2019).

In `chillkernel` the density (z) over the entire plot integrates to one, and therefore represents the relative probability of an observation (yield along y-axis) given a specific chill portion (along x-axis).

Estimated yield given the expected chill

We used the `pasitR` function `chillkernelslice` to calculate the estimated yield given the expected chill, based on a slice of ‘z’ from the Kernel density calculated with `chillkernel`. The `expectedchill` parameter is set to 30.

The `chillkernelslice` function plots the probabilities (shown along the y-axis) for the expected yield (shown along the x-axis). Since this is a cut through the density kernel `chillkernel`, which integrates to 1, the probability values are relative, not absolute measures.

Chill portion intervals

We used the `chillviolin` function to determine possible Chill Portion intervals by calculating the optimal interval width for Chill Portions using the `IQR` function in the `stats` package, after the Freedman-Diaconis

Table 1: Yield records (in tons per hectare) for 8 seasons (2010 to 2017) for two sweet cherry cultivars (Lapins and Brooks).

Year	Variety	Yield
2010	Lapins	16.387600
2011	Lapins	11.401600
2012	Lapins	1.599200
2013	Lapins	13.521200
2014	Lapins	21.648480
2015	Lapins	9.413200
2016	Lapins	24.974440
2017	Lapins	8.515682
2010	Brooks	6.412400
2011	Brooks	1.296000
2012	Brooks	1.032000
2013	Brooks	3.396800
2014	Brooks	6.872400
2015	Brooks	2.887160
2016	Brooks	9.217320
2017	Brooks	9.892581

Table 2: Weather data from a weather station placed in the orchard.

YEARMODA	Weather_Station	Year	Month	Day	JDay	Tmin	Tmax
20100101	Quillota	2010	1	1	1	6.2	31.0
20100102	Quillota	2010	1	2	2	7.6	29.4
20100103	Quillota	2010	1	3	3	12.2	23.2
20100104	Quillota	2010	1	4	4	8.0	24.0
20100105	Quillota	2010	1	5	5	8.0	26.5
20100106	Quillota	2010	1	6	6	9.0	27.0
20100107	Quillota	2010	1	7	7	8.5	24.0
20100108	Quillota	2010	1	8	8	7.0	28.0
20100109	Quillota	2010	1	9	9	8.0	28.0
20100110	Quillota	2010	1	10	10	8.0	24.0

Table 3: Computed chill accumulation for each pre-defined chilling season between May 1 and August 31.

Season	End_year	Season_days	Data_days	Perc_complete	Chill_Portions
2009/2010	2010	123	123	100	68.45256
2010/2011	2011	123	123	100	60.46397
2011/2012	2012	123	123	100	44.61716
2012/2013	2013	123	123	100	52.14200
2013/2014	2014	123	123	100	54.60832
2014/2015	2015	123	123	100	43.24068
2015/2016	2016	123	123	100	53.47477
2016/2017	2017	123	123	100	53.95999

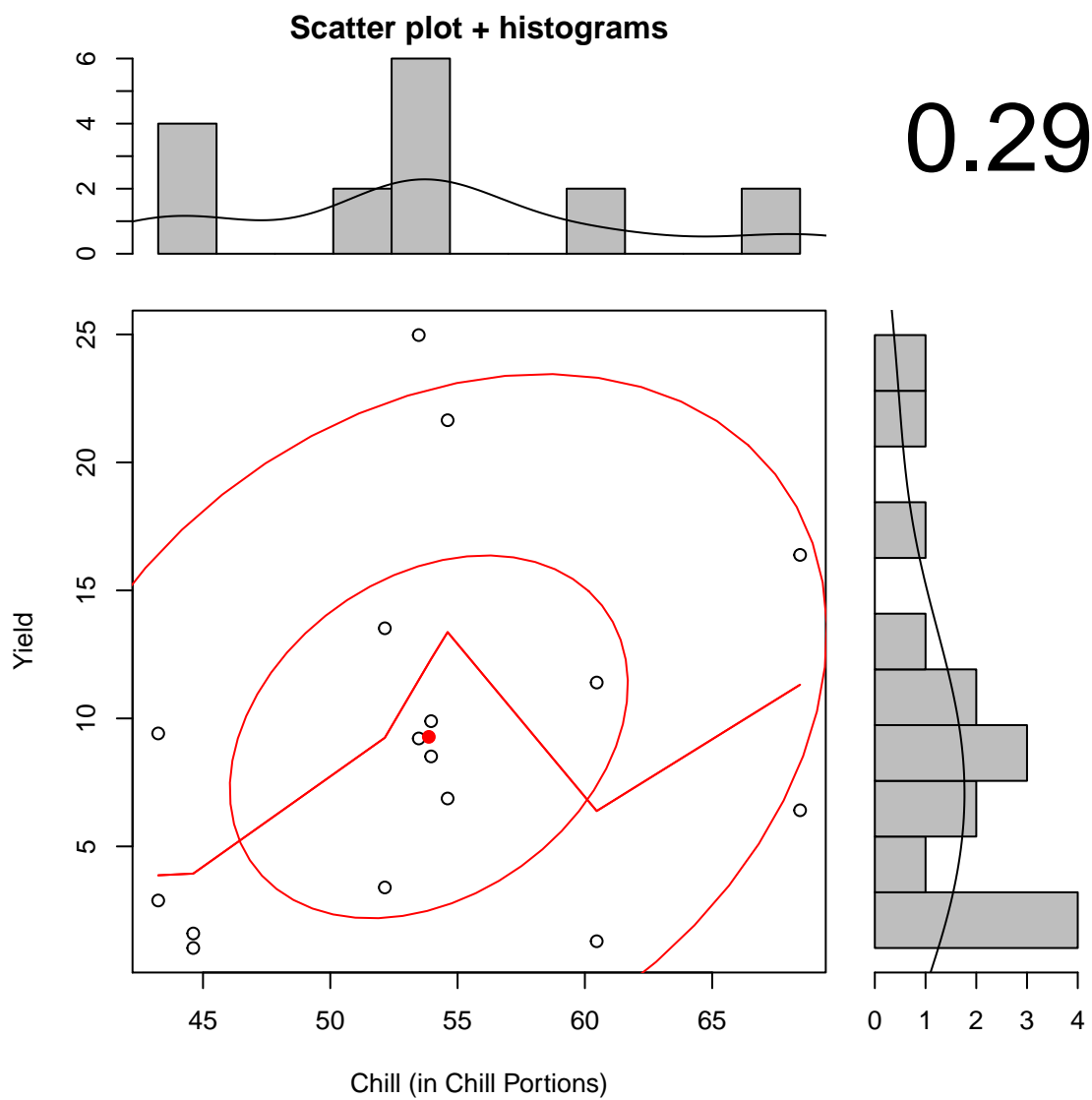


Figure 1: Scatter plot of Chill Portions (x) and yield (y) for sweet cherries.

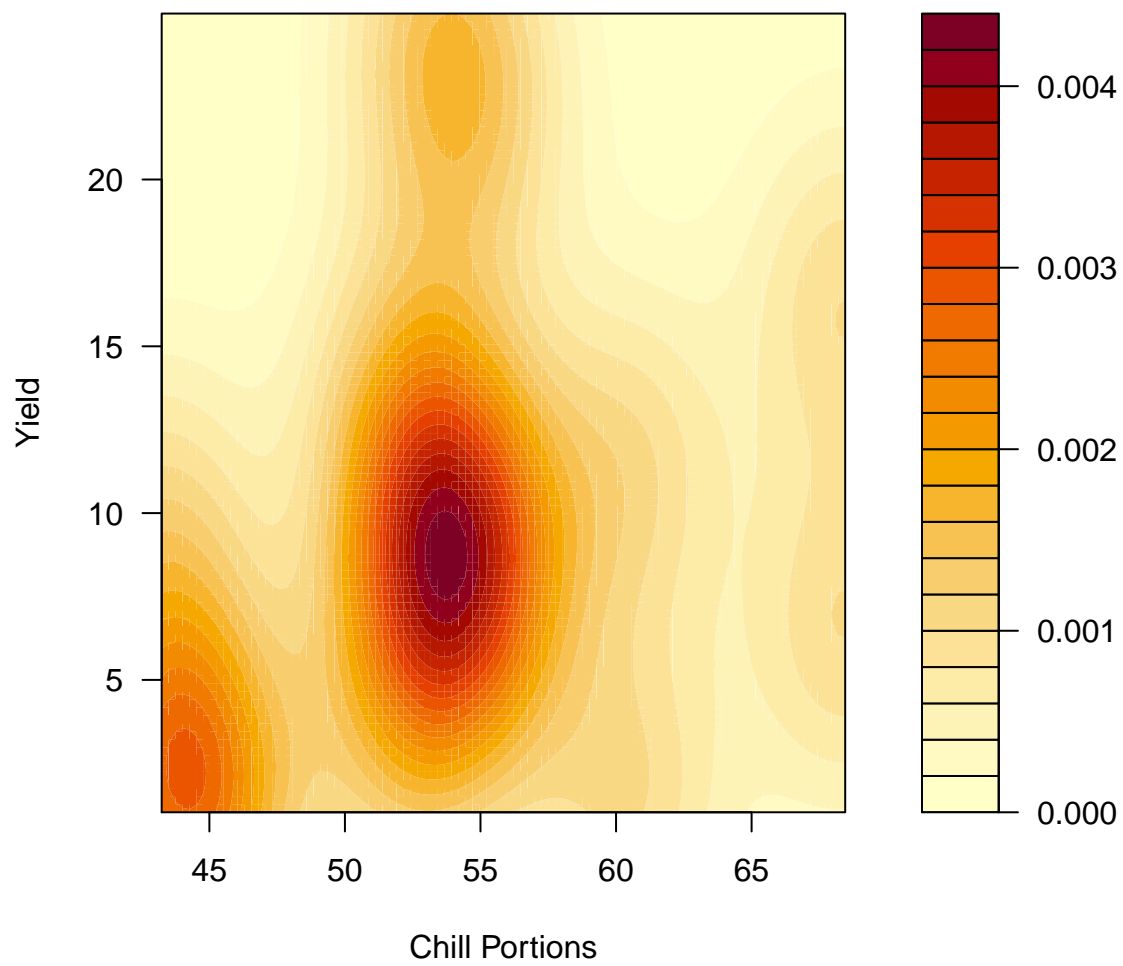


Figure 2: Kernel density matrix of Chill Portions (x) and yield (y) for sweet cherries.

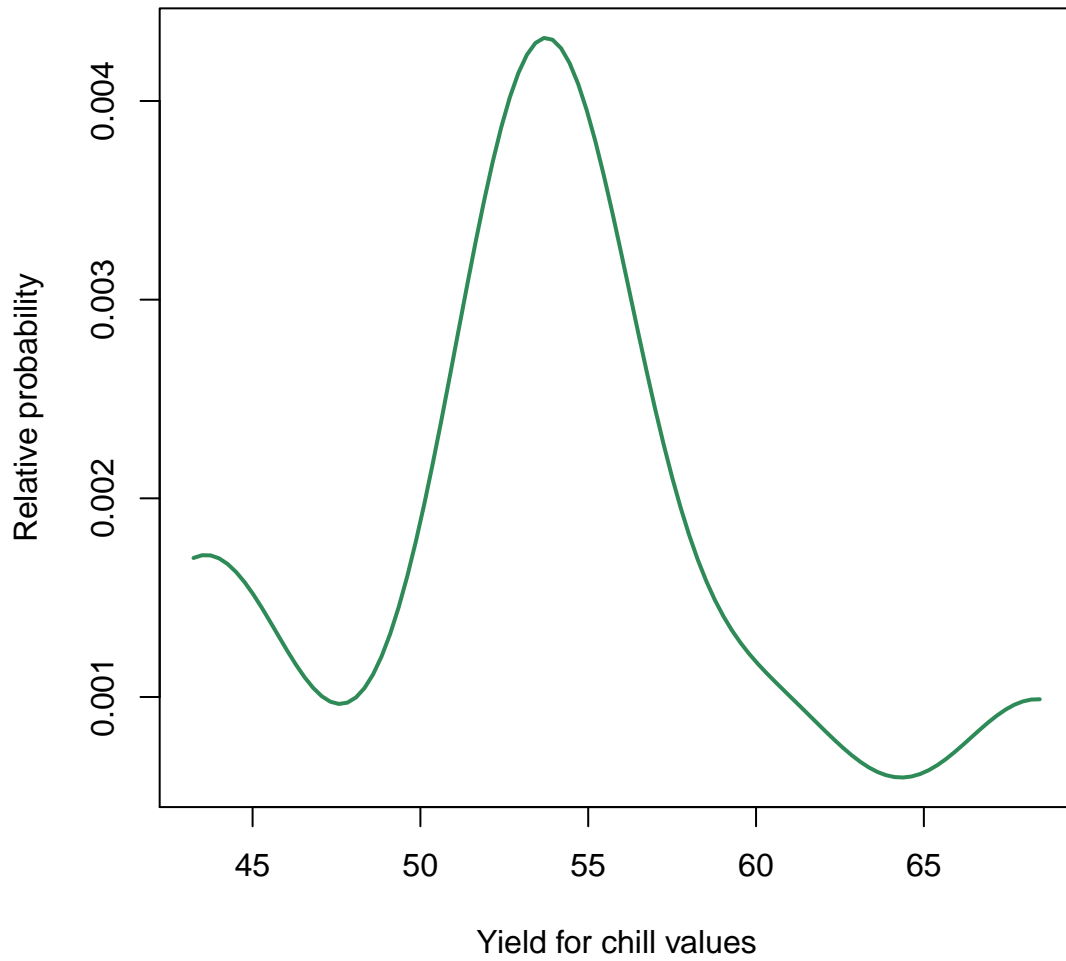


Figure 3: Estimated yield of sweet cherry given the expected chill, based on a slice of 'z' from the Kernel density.

rule (IQR = interquartile range) (R Core Team, 2019). Plot made with `ggplot2` (Wickham et al., 2019).

Probability of yield given chill

We use the `chillkernel slicerange` to show the probable yield given a likely range of expected Chill Portions. The optimized interquartile ranges for Chill Portion intervals (shown in `chillviolin`) can be used to select a range to slice from the density kernel `chillkernel` as was done for a single chill value in `chillkernel slice`. As with `chillkernel slice` the probability values shown are relative, not absolute measures. They are the result of cuts through the density kernel `chillkernel`, which integrates to 1.

Next steps

The `pasitR` functions closely follow `chillR` (Luedeling, 2019) and `decisionSupport` (Luedeling et al., 2019). We will continue to develop these and may intergrate them into future version of these packages. The functions are all stored in an open access repository (<https://github.com/hortibonn/pasitR>) and are free to use and modify by all (Schiffers et al., 2018).

References

- Luedeling, E. 2019. `ChillR`: Statistical methods for phenology analysis in temperate fruit trees.
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- Wickham, H., Chang, W., Henry, L., Pedersen, T.L., Takahashi, K., Wilke, C., Woo, K. and Yutani, H. 2019. `Ggplot2`: Create elegant data visualisations using the grammar of graphics.

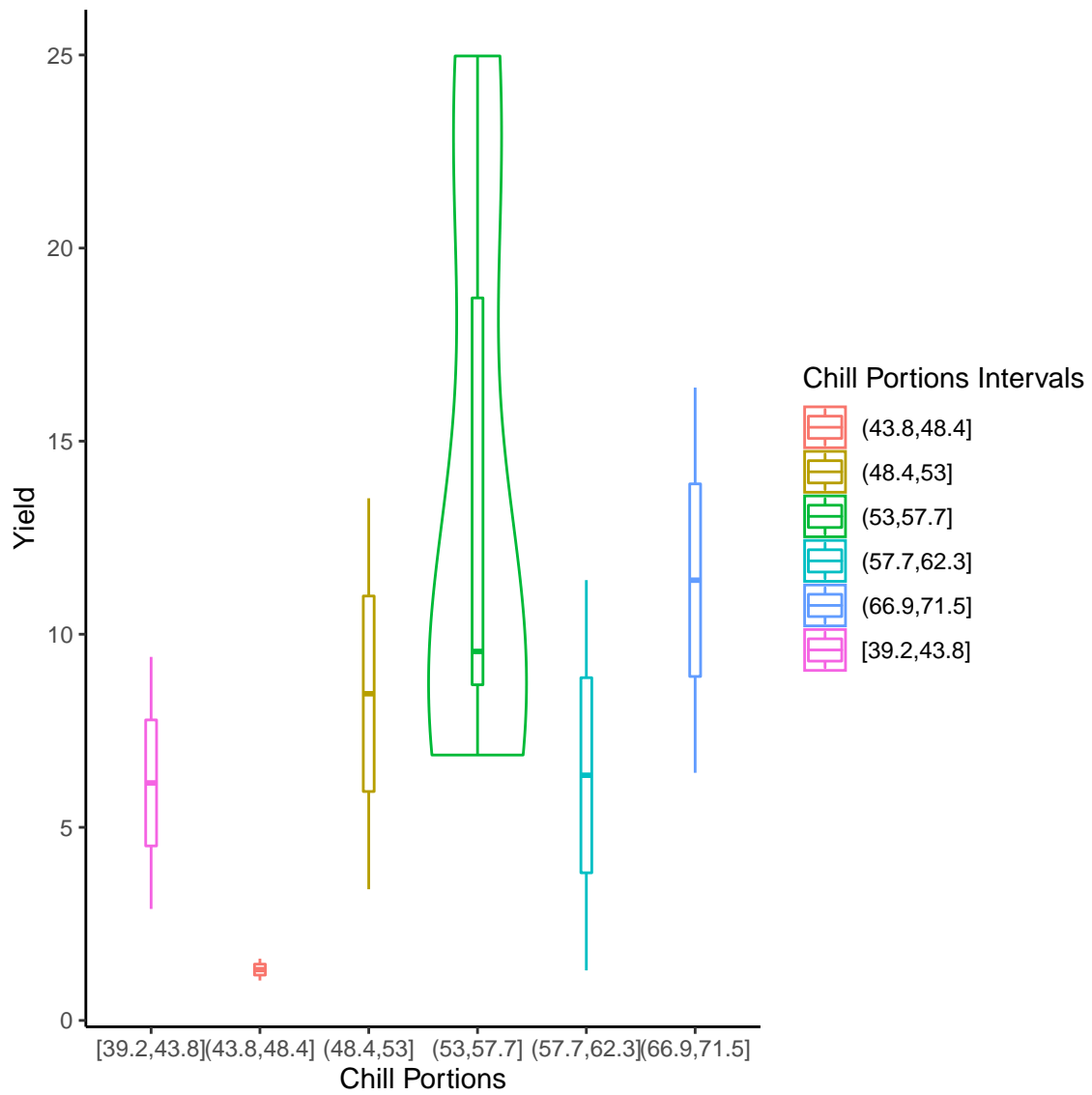


Figure 4: Violin plots with boxplot overlays of possible Chill Portions (x) and yield (y) with six different intervals of Chill Portions.

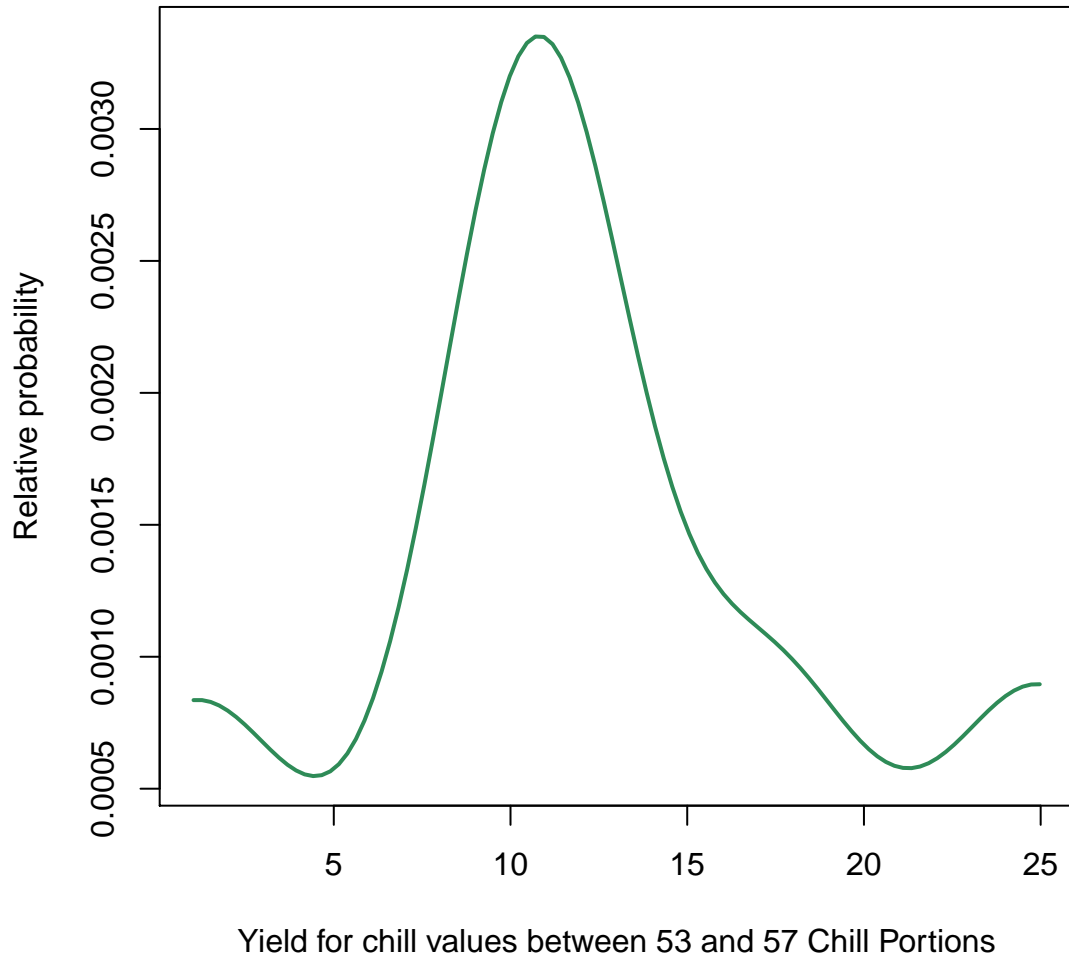


Figure 5: Probabilities (shown along the y-axis) for the expected yield (shown along the x-axis). Here we set the minimum Chill Portions to 53 and the maximum to 57.