Estimating yield as a function of chill accumulation

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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 (Schiffers 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 (Chill Portions) 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 (Schiffers 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 developed the `chillscatter` function to create a scatter plot of chill and yield (Fig. 1). The function calculates the associated estimated densities with loess smooth linear fits density curves using the `scatter.hist` function in the `plyr` package (Wickham, 2019).

We developed the `chillkernel` function 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 bi-variate normal kernel, so this looks slightly different compared to the scatter plot estimates above. 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 amount of chill (along x-axis) (Fig. 2).

Estimated yield given the expected chill

We developed 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` (Fig. 3). The 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` (Fig. 2), which integrates to 1, the probability values are relative, not absolute measures. We set the value of expected chill for which to estimate yield should (the `expectedchill` parameter) to 30.

Chill portion intervals

We developed the `chillviolin` function to determine possible Chill Portion intervals (Fig. 4). We calculate the optimal interval width for Chill Portions using the `IQR` function in the `stats` package, after the Freedman-Diaconis rule (IQR = interquartile range) (R Core Team, 2019). The `chillviolin` function uses the `ggplot2` (Wickham et al., 2019) library.

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

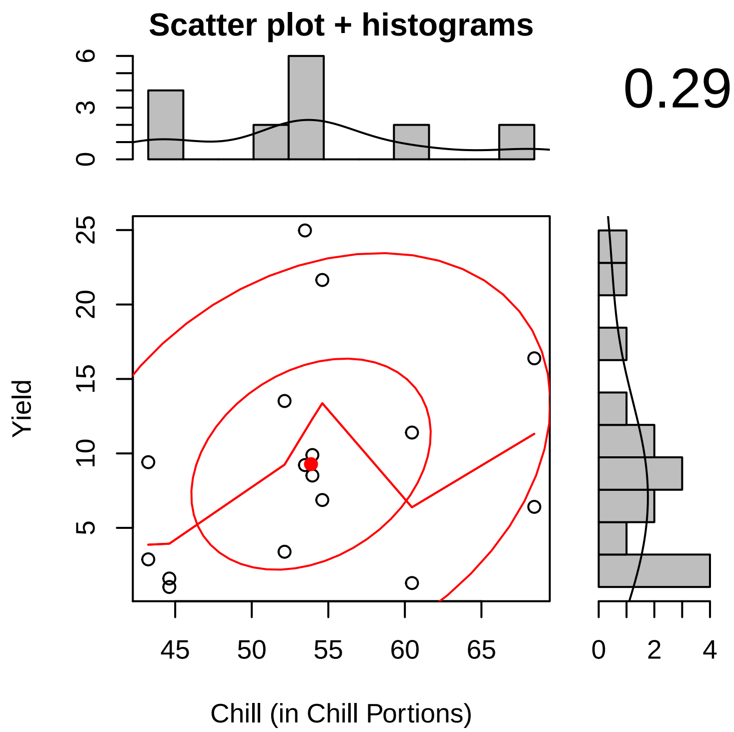

Figure 1: Scatter plot of Chill Portions (x) and yield (y) for sweet cherries.

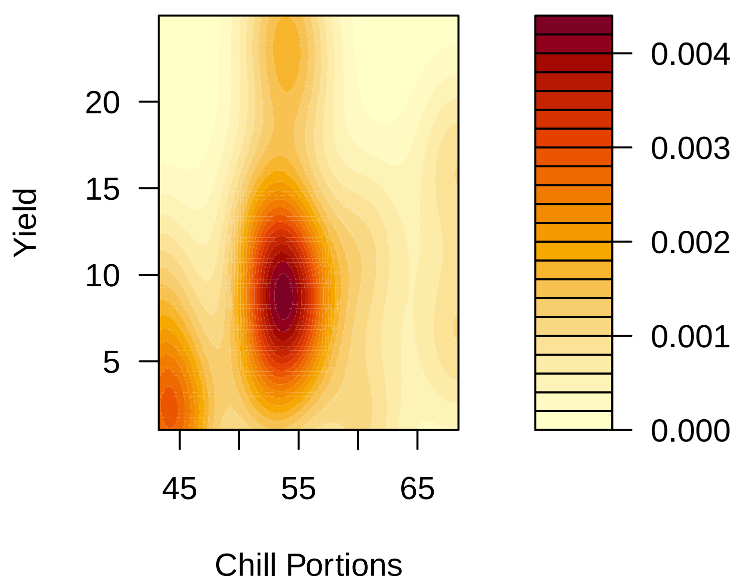

Figure 2: Density surface plot of Chill Portions (x) and yield (y) for sweet cherries. The legend shows the value for the estimated density (z).

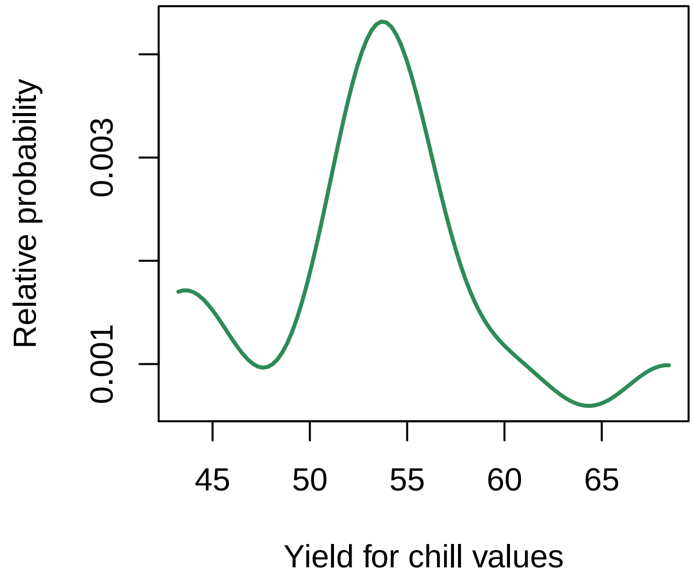

Figure 3: Estimated yield of sweet cherry given the expected chill, based on a slice of ‘z’ from the Kernel density.

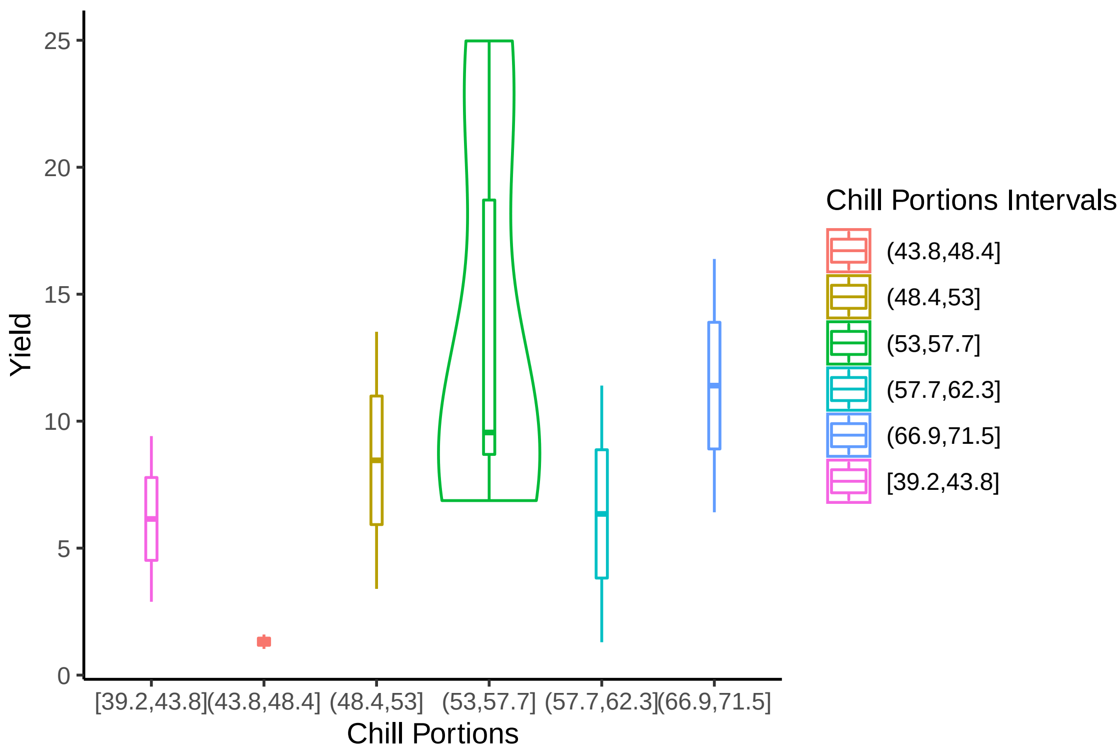

Figure 4: Violin plots with boxplot overlays of possible Chill Portions (x) and yield (y) with six different intervals of Chill Portions.

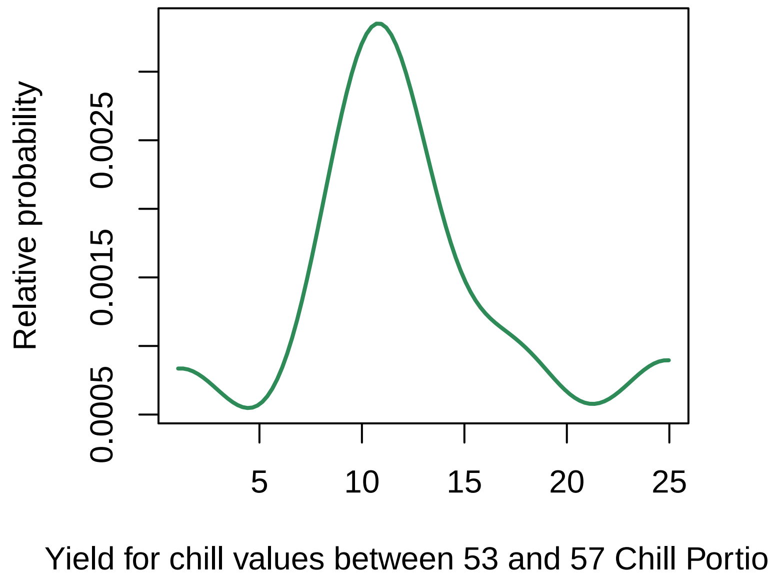

Figure 5: Probabilities (shown along the y-axis) for the expected yield (shown along the x-axis). Here we set the minimum Chill Portions to 53 and the maximum to 57.

Probability of yield given chill

We developed the `chillkernelslicerange` function to visualize the probable yield given a likely range of expected Chill Portions (Fig. 5). The function takes the optimized interquartile ranges for chill intervals to select a range to slice from the density kernel `chillkernel` the same procedures we used for a single chill value in `chillkernelslice` (Fig. 3). As with `chillkernelslice` the probability values shown are relative, not absolute measures. They are the result of cuts through the density kernel (Fig. 2), which integrates to 1.

Next steps

We have demonstrated the possibility for generating forecasts of possible yields given chill. The `pasitR` functions closely follow chillR (Luedeling, 2019) and decisionSupport (Luedeling et al., 2019). We will continue to develop these and may integrate 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 (Schiffers et al., 2018).

References

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