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An Artificial Neural Network Model to Predict Wheat Stem Sawfly Cutting in Solid-Stemmed Wheat Cultivars

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Beres, B. L., Hill, B. D., Cárcamo, H. A., Knodel, J. J., Weaver, D. K., Cuthbert, R. D. 2016. **An artificial neural network model to predict wheat stem sawfly cutting in solid-stemmed wheat cultivars.** Can. J. Plant Sci. xx:xx–xx. The wheat stem sawfly, *Cephus cinctus* Norton (Hymenoptera: Cephidae), is a major pest of wheat (*Triticum aestivum* L.) in the northern Great Plains of North America. The use of solid-stemmed cultivars helps mitigate crop losses and can also affect the survivorship of *C. cinctus*. The efficacy of ‘resistance’ is based on the plant’s ability to develop pith in the culm of the stem, which is influenced greatly by interactions between the genotype and the environment. Precipitation-related weather interacts with photoperiod to reduce pith expression in solid-stemmed wheat. A model that predicts pith expression could serve as a management tool to prevent losses by alerting producers if in-season precipitation patterns have caused less than ideal pith expression in a cultivar. Artificial Neural Network (ANN) models are used to make predictions for complex, non-linear systems with many co-related variables. Our objective was to improve upon past models that used regression analyses by deploying an ANN model to predict in-season stem cutting of wheat by wheat stem sawfly. Results indicate that stem cutting is influenced by the precipitation within a 5-wk period from June 1 to July 5. These results were successfully deployed in a model that should assist with predictions of potential late season stem cutting. Deployment of this ANN model as a transferable executable file may facilitate predictions of stem cutting by wheat stem sawfly in any given year, which will empower producers to implement the appropriate harvest management strategies to reduce losses.

Keywords: *Triticum aestivum* L., host plant, bread wheat, solid-stemmed, sawfly, *Cephus cinctus*.

Abbreviations: WSS, wheat stem sawfly; ANN, artificial neural network; **Pcp**, precipitation; **Pdy**, day with precipitation; **CWRS**, Canada Western Red Spring; **AAE**, average absolute error

The wheat stem sawfly, *Cephus cinctus* Norton (Hymenoptera: Cephidae), has been a major pest of wheat (*Triticum aestivum* L.) in the northern Great Plains of North America for more than 100 years. Within this geographical region, the areas subjected to greatest attack historically, have been southern Alberta and Saskatchewan, southwestern Manitoba, eastern and northern Montana, North Dakota, northern South Dakota, and western Minnesota (Beres et al. 2011). However, regions such as northeastern Colorado, southern Wyoming, and western Nebraska are now experiencing moderate to severe WSS infestations. A comprehensive review of sawfly biology and management was published by Beres et al. (2011). Briefly, adult sawflies emerge in mid- to late-spring from the previous year's host, which is usually a wheat field, and invade surrounding fields planted to wheat. The female will deposit one egg per stem of wheat and can carry as many as 50 eggs. A larva hatches 5 to 7 days after deposition and begins feeding inside the stem. The adult sawfly inflicts little injury on its host plant but the stem boring activity of the larva destroys parenchyma tissue and vascular bundles of the host, causing a significant reduction in photosynthetic capacity (Macedo et al. 2005). This can translate into >15% losses in grain weight (Holmes 1977; Morrill et al. 1992; Seamans et al. 1944). The second form of damage occurs at crop maturity when the larva prepares for overwintering by moving downward to the base of the plant where it cuts a neat v-shaped groove around the inside of the stem at ground level. This does not sever the stem, but weakens it sufficiently to topple easily when exposed to wind (Ainslie 1929). The larva then fills the girdled section with frass, creating a solid plug in the pith cavity that seals the stub when the stem above topples. Below the plug the larva encases itself in a silken-like cocoon and overwinters as a mature fifth instar (Holmes and Peterson 1960)

Additional yield losses are incurred from the unharvested grain heads left on the ground post-harvest (Beres et al. 2011). Ainslie (1920) estimated losses from stem lodging at approximately 30% of attainable yield, and Criddle (1922) estimated losses to be about 25% of the crop in the 1921 outbreak. In subsequent outbreaks prior to the release of the first solid-stemmed cultivar, annual losses in the Canadian prairies exceeded 544,000 tonnes (Platt and Farstad 1949). Damage and losses have continued to increase as a producer survey in Montana projected losses in the mid-1990's to exceed 402,000 tonnes annually (Blodgett et al. 1997). Beres et al. (2007) used the strong positive correlation between stem cutting and grain losses to show that grain losses could be estimated based on stem cutting. Using this approach, and based on modern commodity prices, stem cutting that was close to 50% could result in economic losses in excess of \$400 million annually across the area of distribution now prone to attack.

The use of solid-stemmed cultivars helps mitigate crop losses and can also affect the survivorship of *C. cinctus*. Pith developing in a solid stem is a key source of mortality in the egg (Holmes and Peterson 1961) and larval stages, causing the greatest amount of irreplaceable mortality in solid stem wheat (Buteler et al. 2015). The boring activity of larvae that do survive can be restricted, creating negative effects to fitness and survivorship of the insect (Cárcamo et al. 2005; O'Keeffe et al. 1960). Thus, the efficacy of 'resistance' is based on the plant's ability to develop pith in the culm of the stem, which is influenced greatly by interactions between the genotype and the local environment. All solid-stemmed spring and winter wheat hexaploid cultivars developed to date derive resistance from the Portugese line S-615 (Kemp 1934; Platt and Farstad 1946), but two other sources exist (Clarke et al. 2005). In hexaploid wheat, the inheritance of the solid stem phenotype is more complex than durum (*Triticum turgidum* L.). In S-615, stem solidness has been reported to be controlled by three to four recessive genes (Cook

et al. 2004; Lanning et al. 2006). Quantitative trait loci (QTL) mapping experiments have shown that a single locus on 3BL explains 76% of the total variation for stem solidness (Cook et al. 2004). This QTL is likely allelic to *SStI* given their similar map location (Houshmand et al. 2007). Minor effect genes have been reported on chromosome 3DL (Cook et al. 2004). However, unlike in durum, the complex genetic inheritance can result in inconsistent pith expression in the field in some genetic backgrounds (Hayat et al. 1995). This was observed shortly after the release of Rescue (S615 derivative) when high susceptibility to stem cutting was noted at Regina, SK (Platt and Farstad 1949). The inconsistency is not surprising given that S615 is a landrace, which unlike modern wheat cultivars, was improved by farmers over many generations without concern for pure line selection. Thus, it is not unreasonable to expect heterogeneity within S615. Moreover, heterogeneity within land races is not uncommon, as shown by Gregová et al. (2006) who found that some landraces were comprised of as many as 12 genotypes at the HMW-GS locus of wheat on chromosome 1B. The heterogeneity implies that, for S615, a portion of the plants within each field/plot may not express an ideal solid phenotype simply because they are not carriers of *SStI* (Beres et al. 2013).

There is also the G x E component to expression, whereby genes conferring pith development in hexaploid wheat plant stems are influenced by photoperiod. Intense sunlight results in maximum expression and pith development, whereas shading or cloudy conditions inhibit pith development (Eckroth and McNeal 1953; Holmes 1984). Holmes (1984) used precipitation-related data to create a regression formula to predict cutting levels (a proxy for stem solidness) in solid-stemmed wheat. Holmes indicated that resistance was reduced whenever any one of the 2-week periods between 25 May and 5 July had 7 or more days with measurable precipitation. The conclusion reached was that pith expression is suppressed in conditions of

sustained days with precipitation because the amount of light a plant receives is suppressed.

However, the fit of predicted vs. actual cutting was modest ($R^2=0.55$) using the model, and other attempts to use the regression model to explain variability in solid-stemmed wheat susceptibility have produced inconsistent results (Beres et al. 2009).

The inconsistency in pith development should not dissuade producers from growing solid-stemmed wheat in areas prone to attack as cultivar selection is critical to a successful IPM system for wheat stem sawfly (Beres 2011). Producers in the past have been reluctant to adopt solid-stemmed wheat as there was a perceived yield penalty when growing solid-stemmed wheat and a concern that increased wear on harvesting equipment occurs when threshing solid stems (B. Buckman personal communication). Beres et al. (2009, 2007) and Nilsen et al. (2016) demonstrated that solid-stemmed common and durum wheat can be agronomically superior to hollow-stemmed wheat, particularly in the presence of sawfly pressure. ‘Lillian’ (DePauw et al. 2005), the latest solid-stemmed cultivar, has occupied up to one-third of the wheat hectares in Saskatchewan and 20% of the prairie-wide wheat hectares (Anonymous 2010). However, the inconsistent pith expression, first noted with the release of ‘Rescue’, has been observed with ‘Lillian’ (Nilsen et al. 2016). Given the extensive hectares planted to solid-stemmed wheat during an elevated WSS threat, a model that can accurately predict pith expression could serve as a vital quality assurance tool to prevent losses by alerting producers if in-season precipitation patterns have caused less than ideal pith expression in a solid-stemmed cultivar. Such a tool would allow for preventative measures to be deployed such as swathing ahead of harvest to prevent the loss of cut stems. Recent non-linear models unavailable in the Holmes era could have potential to improve upon the hypothesis around using weather data as parameters to predict stem solidness in wheat and subsequent risk of yield loss.

Artificial Neural network (ANN) models are used to make predictions for complex, non-linear systems with many co-related variables. Agricultural systems usually involve many variables including weather which makes ANN models particularly applicable for predicting agricultural outcomes. ANN modeling has previously been used to predict beef carcass tenderness (Hill et al. 2000), maturity and seeding date of spring wheat in western Canada (Hill et al. 2002; Major et al. 1996), harvest dates and quality of greenhouse peppers and tomatoes (Ehret et al. 2008; Lin and Hill 2007; Lin and Hill 2008), and bacterial ring rot symptom expression in potatoes (Hill et al. 2011). Therefore, the objective of this study was to use ANN modeling to predict the in-season tolerance level of solid-stemmed wheat cultivars to wheat stem sawfly, expressed as ‘% stems cut by the sawfly’.

MATERIALS AND METHODS

Data acquisition and analysis. Stem cutting data (n=28, % of stems cut by sawfly) on the bread wheat cultivar Rescue for the period 1949-1978 at Lethbridge, AB were obtained from Holmes (1984) and designated as ‘Holmes data’. Weather records (precipitation, h of sun) for this period were obtained from the Lethbridge Research and Development Centre, Agriculture & Agri-Food Canada, Lethbridge, AB. Stem cutting data (n=18) on the wheat cultivars Rescue (Platt et al. 1948), Lancer, Leader, AC Abbey (DePauw et al. 2000), AC Eatonia (DePauw et al. 1994), Lillian (DePauw et al. 2005), BW828, BW765, and S615 for the period 1987-2007 in southern Alberta and Saskatchewan were obtained from anonymous field trial data and the western bread wheat cooperative registration trials. These data were designated as the ‘Beres data’. Precipitation data were obtained from the Environment Canada website <http://www.climate.weatheroffice.gc.ca> for Bow Island, Foremost, Lethbridge, and Monarch in Alberta, and for Esk, Indian Head, Scott, and Swift Current in Saskatchewan.

As per Holmes (1984), weather-related inputs were examined for the 6-wk period

extending from May 25 to July 5 for each year. Instead of tabulating precipitation over three consecutive 2-wk periods (Holmes 1984), we tabulated precipitation on a weekly basis. The following 14 rain-related inputs were assembled for ANN modelling: Pdy1-6 (no. days with measurable precipitation for weeks 1-6) and Pcp1-6 (total mm of precipitation over each week) for the weekly periods of May 25-31 (week-1), June 1-7 (week-2), June 8-14 (week-3), June 15-21 (week-4), June 22-28 (week-5) and June 29-July 5 (week-6), TotalPdy (total no. days with precipitation for the entire May 25-July 5 period), and TotalPcp (total mm of precipitation for the entire May 25-July 5 period). Wheat cultivar and plot locations were not used as model inputs because we wanted the ANN models to be generalized over these factors. The predicted output was ‘% of stems cut by the sawfly’, averaged over replicate plots and cultivars for each year at each location.

A thorough validation was performed in 2010 by correlating model predictions of ‘% stems cut’ with stem solidness ratings for Bow Island, Foremost, Coaldale and Lethbridge in Alberta; and for Indian Head, Scott, and Swift Current in Saskatchewan. Stem solidness ratings were performed by randomly collecting fifty main stems from a field of solid-stemmed spring wheat, which is considered an acceptable sample size, (Cárcamo et al. 2007), and splitting the stem longitudinally from the base to the spike. The degree of pith fill inside the culm was scored on a scale of 1 (hollow) to 5 (solid). Solidness, and therefore susceptibility to cutting, was averaged over all internodes so that each stem had a mean solidness rating. The solidness ratings were then averaged over all stems for each site to give a mean solidness rating for location sampled. Using solidness ratings from stem dissections is the most precise method for assessing stem solidness because observations of stem cutting can be confounded if sawflies are attacked and killed by natural enemies prior to cutting the stem. This results in erroneous low cutting

ratings or high resistance ranking in environments that caused poor pith expression. The results from field sampling in 2010 were examined to determine the ability of the ANN model to predict stem cutting in solid-stemmed wheat by the wheat stem sawfly.

Data were arranged in Excel[®] so that values for the 14 inputs were associated with the ‘% stems cut’ for each location in each of the years. Each line of 14 inputs paired with an output formed an example case for training the ANN. Data from Holmes (1984) were combined with the more recent Beres data. The total data (example cases) $n=46$ were derived mostly from Lethbridge (34 records), but also from Swift Current, SK (5 records), Foremost, AB (3 records), Nobleford, AB (3 records), and Esk, SK (1 record). The data were fairly evenly distributed over the % stems cut 0-100% scale (16, 12, 9, 8, 1 cases for the 0-20, 21-40, 41-60, 61-80, 81-100% ratings, respectively). Data were prepared for NN modelling by reducing all input numeric data to one decimal, then randomizing the order of the training data.

ANN modelling. General descriptions of ANN modelling can be found in Lawrence (1993), Smith (1993) and Kohzadi et al. (1995). We constructed feed-forward ANN models using NeuralWorks Predict[®] v3.21 software (NeuralWare[®], Carnegie, PA) on a desktop PC (2.4 GHz). The process involved: 1) selecting training and validation subsets; 2) analyzing and transforming data; 3) selecting variables; 4) network construction and training; and 5) model verification. Details on how Predict[®] conducts ANN modelling has been previously published (Hill et al. 2002). A 5x cross-validation procedure was used to evaluate the NN. That is, 20% of the data ($n=9$) were held aside during ANN training as a validation set to evaluate the developed models, then this 20% data was returned to the training set and the process repeated by setting aside the next 20% of the data, etc., until every datum appeared once and only once in a validation set. The ANN inputs and parameter settings were evaluated by averaging net

performance across all 5 validation sets. Artificial neural network modeling is an iterative trial and error process initiated using different random seed numbers. For all predictions, we ran 30 different seed numbers at a time. Usually, no one absolute best ANN model was obtained but rather a few different models with similar performance. The ‘best’ ANN models were chosen on the basis of a suitable ANN architecture (i.e., a minimum number of input neurons connected to a hidden layer that had fewer neurons than the input layer), combined with a high R^2 for predicted vs. actual ‘% stems cut’ and a low average absolute error (AAE), for the records in the validation set.

To estimate the relative importance of the different inputs to model predictions, sensitivity analysis was conducted. This Predict[®] software option allows the determination of the effect that a small change in an input value will have on the output and to numerically rank the inputs according to this sensitivity. Mathematically, the output of sensitivity analysis is a matrix of partial derivatives of output values with respect to input variables. The sensitivity rankings were combined across the 5 ‘best’ cross-validation models. The lowest ranked inputs were manually dropped and the models reconstructed to confirm the lack of influence of the deleted inputs. This process (dropping inputs) was repeated until model performance for predicting the % stems cut dropped off.

RESULTS AND DISCUSSION

Determination of appropriate inputs and the ‘best’ model. Preliminary modeling indicated that h of sun did not contribute much to our models. The original 14 rain-related inputs could be reduced to 7 inputs to predict % stems cut and good NN models were still obtained. The 5 ‘best’ cross-validation models using the 7 inputs (Pcp2, Pcp3, Pcp4, Pdy6, Pcp6, TotalPdy, TotalPcp) had an average R^2 of 0.60 (SD=0.10) with an AAE of 14.8% (0-100% scale).

Our ANN model performance (average R^2 of 0.60) was much improved compared with

the regression model of Holmes. When we used SAS[®] (Littell et al. 2002) to fit Holmes' regression model to our combined data set (n=46), the resultant R^2 was only 0.26. However, our average R^2 was for records our ANN had not seen during model training, whereas Holmes' R^2 was for records that were part of the model fitting process. It is notable that we were able to combine data into the ANN model from two different eras (1949-1978 and 1987-2007), different cultivars and locations, and still achieve good model performance.

Deployed ANN model. To obtain a 7-input deployed model that encompassed the complete range of data, the ANN were shown all 46 records during training and the 'best' model was selected from the 30 ANN runs (generated with 30 different seed numbers). This deployed model had an architecture of 10-6-1 (two transformations used for Pcp2, Pcp3, and Pcp6; and one transformation of Pcp4, Pdy6, TotalPdy, and TotalPcp) with an internal validation (all records previously shown to model) R^2 of 0.90 and an AAE of 5.7%. Of greater importance as an indication of predictability ie. records the model has not been shown, the external validation revealed an R^2 of 0.92 and AAE of 3.8. The model was exported from the Predict[®] software in Visual Basic[®], an input/output user-interface added (Fig. 1), and the program compiled into an executable file to facilitate predictions for unknown cases of % stems cut. The user-interface permits the entry of different weather scenarios and the exported ANN model runs seamlessly in the background once the user requests the calculation. For accurate predictions, the range of input values should be within the ranges used in our training set (ranges indicated on user-interface, Fig. 1). It is notable that we were able to develop a robust model using historical precipitation data from Environment Canada weather stations. This indicates that the weather station data is a reasonable representation of local weather, which facilitates the ease at which a producer can access precipitation-related input values for his/her respective region.

Relative importance of model inputs. Sensitivity analysis was conducted to rank the 7 inputs for their importance to the ANN models (Table 1). The total precipitation during June 1-7 (Pcp2) was the most important input with the other inputs having less influence on model solutions. Total precipitation during June 29-July 5 (Pcp6) was the second most important input. This agrees with our understanding of conditions that influence pith expression and susceptibility to stem cutting by wheat stem sawfly. Of notable importance were two periods of rainfall (Pcp2, Pcp6) separated by a month (Table 1). The reason for this is not clear but implies that, historically, there may have been two main periods that influence pith expression, which may relate to seeding dates. It is also not obvious why the ANN require Pdy6 as well as Pcp6 for good model performance. The fact that Pdy1 and Pcp1 were not required by the model suggests that pith expression was not affected by weather until June 1.

Model validation using additional records. Deployment of our best ANN model as a transferable executable file should help facilitate predictions of stem cutting by wheat stem sawfly in any given year. Model validation was performed by correlating model predictions of ‘% stems cut’ with 2010 stem solidness ratings for Bow Island, Foremost, Coaldale and Lethbridge in Alberta, and for Indian Head, Scott, and Swift Current in Saskatchewan (Table 2, Fig. 2). Despite the uneven distribution of data, the R^2 of 0.92 ($n=7$) indicates that the model could predict pith expression, and therefore susceptibility to stem cutting by sawfly in solid-stemmed wheat with a high degree of accuracy as it exceeds the critical R^2 for $n=7$ observations (0.60) (Steel et al. 1997). The value of the model is reflected in years like 2010 when pith expression in solid-stemmed wheat was less than ideal due to the precipitation patterns experienced across most of the Canadian prairies. Wallace et al. (1973) noted that the minimum level of stem solidness rating required in solid-stemmed wheat should be 3.75; none of the sites

sampled in 2010 achieved this level of pith expression (Table 2, Fig. 2). The model accurately predicted cutting levels, which would have alerted producers in those regions (Saskatchewan) that higher than desirable cutting in solid-stemmed fields may occur if there is sawfly pressure in the area. Producers would then have the option well in advance of harvest to scout fields to determine the presence of wheat stem sawfly and implement management strategies (swathing) as necessary to mitigate losses.

For a thorough pest monitoring and surveillance strategy, the ANN model should be used in conjunction with risk forecast maps, which are available in Canada for wheat stem sawfly (Meers and Tames 2010), and are ideal for the large areas of similar cropping ecosystems in the Canadian prairies. The map forecast allows producers to anticipate wheat stem sawfly pressure and adopt solid-stemmed cultivars as required; and the ANN model follows with a prediction for the level of stem solidness expected in the area that the cultivar is grown. Predicted levels that exceed 20-25% predicted stem cutting would warrant preventative measures at harvest to minimize losses from stem cutting. Future directions will be focused on a ANN proto-type for North Dakota and/or Montana by broadening the data set to integrate cultivar responses and weather data specific to these regions and agroecosystems.

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Table 1. Relative importance of inputs in the 7-input models. Relative ranking determined by the Predict[®] sensitivity analysis option.

Sensitivity analysis on the 7-input models

Input	Period	Rank
1. Pcp2	June 1-7	5.58
2. Pcp6	June 29-July 5	3.33
3. Pdy6	June 29-July 5	0.67
4. Pcp3	June 8-14	0.34
5. TotalPcp	June 1-July 5	0.34
6. TotalPdy	June 1-July 5	0.09
7. Pcp4	June 15-21	0.09

The following 7 rain-related inputs were selected for final NN modelling: Pcp2-4, and 6 (total mm of precipitation over each week) for the weekly periods of June 1-7 (week-2), June 8-14 (week-3), June 15-21 (week-4), and June 29-July 5 (week-6), Pdy6 (no. days with measurable precipitation for week 6); TotalPdy (total no. days with precipitation for the entire June 1-July 5 period), and TotalPcp (total mm of precipitation for the entire June 1-July 5 period).

Table 2. Summary of cutting predictions and the validation set from solid-stemmed wheat fields sampled in Alberta and Saskatchewan, Canada in 2010 to test wheat stem sawfly cutting prediction accuracy using the deployed artificial neural network (Fig. 1).

Location	Predicted Cutting	Predicted Cutting	Pith Rating For Each Internode					
	Holmes' Regression Model ^a	WSS4 ^b Neural Net Model	1	2	3	4	5	Avg ^c
Swift Current, SK	74	49	2.72	2.10	1.64	1.54	1.00	1.80
Bow Island, AB	34	16	3.49	3.03	2.29	2.12	* ^d	2.73
Indian Head, SK	55	48	2.06	1.70	1.34	1.25	*	1.59
Coaldale, AB	83	24	3.32	2.84	2.27	1.80	*	2.56
Lethbridge, AB	83	24	2.91	2.67	2.79	2.91	*	2.82
Foremost, AB	61	40	2.74	1.93	1.41	1.44	*	1.88
Scott, SK	67	53	1.68	1.88	1.62	1.57	1.71	1.69

^aHolmes (1984) regression procedure applied to the same data set as the NN modeling, and resultant model used to predict 2010 stem cutting. Canadian Entomologist 116:677-684.

^b WSS4 – refers to 4th iteration of model deemed to be the best fit for prediction accuracy.

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^c Wallace et al. (1973) reported that a minimum 3.8 average solidness was required for adequate control. Journal of Economic Entomology 66: 1121-1123

^d denotes when a 5th internode was not present and no stem pith rating available.

Figure 1. An executable neural network interface for the prediction of potential ‘% stems cuts’ in solid-stemmed wheat cultivars by wheat stem sawfly. The 7 inputs should be within the ranges indicated on the interface. A copy of the executable file is available from the corresponding author.

Figure 2. Relationship between NN model predicted ‘% cutting’ vs. actual 2010 stem solidness ratings for Bow Island, Foremost, Coaldale, and Lethbridge locations in Alberta; and for Indian Head, Scott, and Swift Current in Saskatchewan.

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WSS %Stems Cut Predictor4 (Beres & Hill, 2017)

7 Rain-Related Inputs

Wk1: May25-31	Wk4: Jun15-21	Week2: Total Pcp, mm (0 - 182.6)	43
Wk2: Jun1-7	Wk5: Jun22-28	Week3: Total Pcp, mm (0 - 66.6)	5
Wk3: Jun8-14	Wk6: Jun29-Jul5	Week4: Total Pcp, mm (0 - 81.0)	21
Wk2-6: Total No. days c Pcp (7 - 25)	17	Week6: No. days with Pcp (0 - 7)	5
Wk2-6: Total Pcp, mm (28.5 - 279.2)	146	Week6: Total Pcp, mm (0 - 72.9)	29

Predicted Result

% Stems Cut: 72 (min-max: 7-77)

233x172mm (72 x 72 DPI)

234x134mm (150 x 150 DPI)