Introduction

Cherry blossom blooming has been shown to vary with species and linked to climate. Studies have supported significant association of flowering in cherry trees with climate factors such as temperature, wind, and precipitation. Miller-Rushing, et al. (2007)[1] found evidence for temperature impacting flowering, especially during February and March. Previously, several works have applied different approaches to predicting peak bloom for varied cherry tree species in various locations. For instance, Chung, et al. (2011)[2] applied a two-step phenology model, per research by Cesaraccio, et al. (2004)[3] and Jung, et al. (2005)[4], to predict peak bloom dates for cherry trees in Washington, D.C. and the Mid-Atlantic region. This report focuses on predicting peak bloom dates for the next decade of cherry blossoms at four sites in Washington, D.C. (USA), Kyoto (Japan), Liestal-Weideli (Switzerland), and Vancouver, BC (Canada), with consideration of multiple climate factors.

Data

Data for modeling the day of peak bloom were obtained through a variety of sources. Historical data for peak bloom dates were obtained through a GitHub repository for the Cherry Blossom Prediction Competition hosted by George Mason University. Historical data for day of peak bloom dates back to 812 AD for Kyoto, 1894 for Liestal, and 1921 for Washington, DC. No historical data for day of peak bloom were available for Vancouver, BC. The definition of peak bloom differed for each site. For Kyoto, peak bloom is defined as the day by which 80% of the cherry blossoms are in full bloom. In D.C. and Vancouver, BC, the definition of peak bloom is 70% of the cherry trees and in Liestal, 25% of the trees. In statistical modeling, peak bloom dates were weighted, with 70% bloom set as the baseline. Research and past data have shown that the time from first bloom to peak bloom for cherry blossoms typically lasts about one week. It was assumed that cherry blossoms progressed from first bloom to peak bloom linearly, so weights were assigned to historical dates based the percentage of linear progression to (or from) 70% bloom.

For the three locations with available peak bloom date data as well as Vancouver, BC (Canada), publicly available climate data on factors including wind speed, sea level pressure, precipitation, snow depth, temperature, sun light duration, plant hardiness, and growing degree days are explored for this project. The data for each location are based on a nearby weather station, and those stations' observations on all the mentioned factors are gathered from multiple datasets. The weather stations are at the following locations: Reagan National Airport for Washington, D.C., Basal Binningen for Liestal-Weideli, Vancouver International Airport for Vancouver, and in Kyoto for Kyoto. Wind speed and sea level pressure observations come from the Global Surface Summary of the Day (GSOD) dataset. Precipitation, snow depth, and temperature observations primarily come from the Global Historical Climatology Network (GHCN) dataset. Sunlight duration data used is from the National Oceanic Atmospheric Administration's (NOAA) solar calculator. Plant hardiness zones for the locations are found through the

Plantmaps website. Growing degree days data is obtained through the chillR package in R. Synop reports from Ogimet obtained through the climate package in R is used as available when temperature data is missing in the GSOD dataset for nearby weather stations. A summary of the sites where peak bloom predictions were modeled are shown in Table 1.

Missing data was handled in a variety of different ways depending on the length and number of missing values and the nature of the distribution of the known data. Where there were only a relatively limited number of missing values and the runs of missing values were not lengthy, linear interpolation was used to fill in missing values. Linear interpolation of missing values was used particularly for imputing missing Tmin, Tmax and Tavg data as well as data on other covariates including SLP and precipitation. When there longer stretches of missing data such as long runs of missing daily data or years of missing data, missing values were sometimes imputed if the run was not too long and when the trend of the data approximated a stationary series with white noise. Trended series or series with a clear random walk or moving average were either imputed over flat areas of the trend only or were predicted through fitting the series to an ARIMA model and forecasting the missing values from the time series. When the series for the data was relatively flat with no trend and if the distribution of the data was approximately normally distributed, we took the empirical mean and standard deviation of the data and imputed missing values by randomly sampling from a normal distribution with the same mean and standard deviation as the data. When the trend of the time series was relatively flat and runs were short but the distribution of the data not quite normal, we performed Monte Carlo simulation by taking 10,000 random samples from the known historic data and then we randomly sampled data for missing values from the sampled distribution of the data. When gaps in missing data were serious and lengthy and a time series of the data was highly stochastic or showed signs of unpredictable random walks, moving averages, or nonconstant variance, missing values were left in the data. If there were only a couple of years of missing data for the covariate, a model was sometime run with the variable if the variable was deemed important to prediction. Often, however, variables with missing data had to be dropped from the analysis entirely due to poor data quality.

Location	Latitude (°)	Longitude (°)	Altitude (m)	Cherry Blossoms' Species
Kyoto	35.0120	135.6761	44	*Prunus jamasakura*
Liestal-Weideli	47.4814	7.730519	350	*Prunus avium*
Washington, D.C.	38.8853	-77.0386	0	*Prunus × yedoensis* 'Somei-yoshino'
Vancouver, BC	49.2237	-123.1636	24	*Prunus × yedoensis* 'Akebono'

Table 1. Locations and Species of Cherry Trees of Interest.

Methodology

One main predictor considered was temperature. To begin, we attempted to explore temperature as a predictor based on the chill days model developed by Cesaraccario, et al.[3] and modifications to the model by Chung, et al.[2] This two-step phenology model proposes that buds enter a dormancy phase typically on a set date in the fall, when temperature goes below a threshold temperature (Tc), and accumulate chill days (Dc) until a chill requirement (Rc) is satisfied. Once this chill requirement is satisfied, the buds begin to develop with accumulation of anti-chill days (Dh) and may reach peak bloom once a heat requirement (Rh) is met. The daily chill days or anti-chill days values were calculated based on daily maximum, minimum, and average temperatures as described by Cesaraccario, et al.[3]. The optimal dormancy initiation dates and parameters to use to predict peak bloom dates for each location (with historical peak bloom date data available) were identified as those which minimized root mean square error between observed and predicted peak bloom dates. As an alternate, temperature was also explored based on the Growing Degree Day (GDD) model through the GDD function in the chillR R package. function uses average hourly temperatures, and GDD values were obtained through the equation GDD = Thourly/24 - Tbase, where "Thourly" refers to hourly temperatures for the day and "Tbase" refers to the base temperature above which growing degree days accrue. The chillR package generated hourly temperatures from daily temperature data available based on an idealized temperature curve using a sine function for warming occurring between sunrise and sunset and a logarithmic decay function for cooling overnight[5-6].

Covariates

Several covariates were considered for statistical modeling of the day of peak bloom. Prior research on *Prunus* phenology has strongly suggested that temperature is the primary cause for the timing of blooming. A number of temperature-related and temperature proxy variables were tested for model fit including cumulative average temperature (), cumulative daily minimum temperature [equation], cumulative daily maximum temperature [equation], absolute difference of cumulative daily max and min temperatures (TDIFF) (),, plant hardiness zone, growing degree days (GDD), heating days, chill days, and an optimized estimate of peak bloom day based on the sum of heating days and chill days. We chose to use cumulative daily measures of temperature rather than average or median measures of temperature because research on plant phenology suggests that bloom times are likely due to an accumulation of temperature rather than daily average temperature.[citation] Several studies have even shown that many plant species exhibit minimum/maximum temperature thresholds after which there is no further daily accumulation towards the chilling/heating requirement.[citation] As a result, measures of temperature that reflect some cumulative accumulation of temperature are more likely to have predictive power of bloom time than average or median temperatures.

Out of all the temperature-related variables considered, cumulative average temperature, cumulative absolute temperature difference, GDD, heating days, chill days, and optimized peak bloom date were all significant predictors in modeling, though not all were used. Heating days and optimized peak bloom day, for instance, both displayed high collinearity with GDD. But since

GDD was a much stronger predictor for PBD, heating days and optimized peak bloom were not used in modeling. Cumulative minimum and cumulative maximum temperatures showed predictive power in some models, but not all. Cumulative min and max temperatures were abandoned in favor of much stronger covariates such as cumulative average temperature and cumulative absolute temperature difference. GDD, and TAVG were significant predictors in all models used in this study. GDD was found to correlate highly with the peak bloom dates (Liestal: r=0.996; Kyoto: r=0.950; Washington: r=0.950) and proved to be the strongest predictor in our models. Chill days was significant and appropriate for predicting peak bloom day in Washington, Kyoto, and Liestal, but not in Vancouver. TDIFF was a significant predictor for Washington and Liestal, but not the other cities. Plant hardiness zone was found to be a significant predictor but there were problems incorporating a categorical variable into time series modeling so the variable was ultimately not included in any of the models.

Studies have suggested other factors may contribute to the timing of blooming such as hours of sunlight, wind speed, and the urban heat island effect.[citation] Several sunlight-related variables were tested for model fit including average number of sunlight hours between January 1st and April 1st, average number of hours of sunlight between May 1st and September 30th from the prior summer, mean percentage of possible sunshine, and total hours of sunlight from Jan 1st to March 31st. The average number of sunlight hours from May-September proved to be a significant predictor for Washington, Liestal and Vancouver, but for Kyoto, total number of sunlight hours (Jan-Mar) had more predictive power. Total hours of sunlight was only fit as a covariate for Kyoto so it is possible that this predictor has more predictive power for other sites as well. Average hours of sunlight from Jan-Mar was also significant for Washington, DC.

Sea level air pressure (0.1*mbar) was a significant predictor of bloom time in every model where there was data available for this metric. Unfortunately, sea level air pressure was not available for a long enough series for Liestal or Vancouver so the covariate could not be incorporated into models for these sites. We are not currently aware of any research on effect atmospheric air pressure may have on bloom times for cherry trees, but the fact that these predictors were significant in modeling is perhaps indicative that some association exists, and it is perhaps an area that merits more research.

A study has suggested that wind speed may be a significant predictor for bloom time.[citation] However, due to the paucity of data on wind speed, we were only able to include wind speed as a covariate in the model for Washington, DC.

Variable selection was performed using backward stepwise regression on linear models. Covariates present in the models with a balance of the lowest AIC and highest adjusted [R-sqaured] were selected for modeling. If variables displayed high variance inflation factor (VIF), these covariates were removed from the model and backward stepwise regression was reimplanted with the offending variable left out. The process was iterated until a model of best fit had no covariates displaying collinearity.

Statistical Analysis

Basic linear models were first fit to the data for Washington, DC, Kyoto, Japan, and Liestal, Switzerland. Models of best fit were selected for each site from backward stepwise regression. Covariates in the model of best fit were subsequently forecasted to 2032 using multiple linear regression with AR, MA, ARMA, ARIMA, or SARIMA adjusted errors. Covariates were predicted using all reasonably associated variables for which historic climate data was available for the site. Models for covariate forecasting were checked for assumptions of linear modeling such as independent, normal, and homoscedastic errors, and linearity. Forecasted covariates were then refit to the original linear models of best fit, yielding forecasted fitted values for the day of peak bloom.

To improve prediction accuracy, multiple linear regression models with seasonally autoregressive integrated moving average (SARIMA) adjusted errors were each fit to the data for Washington, Kyoto, and Liestal. Linear models of best fit were first selected for each site. The best fitting model was then fit as a multiple linear regression model with SARIMA errors on the same set of covariates. Peak bloom dates were then forecasted from these model using historical data alone and the SARIMA structure of these models.

Predictions for Vancouver, BC were much more difficult as there are presently no historical data on peak bloom days for this site. We took two different approaches to forecast bloom times for Vancouver. The first method used employed a linear regression model. To forecast peak bloom days, a single multiple linear regression model of best fit was fitted to peak bloom dates and a design matrix of covariates from Washington, Kyoto, and Liestal. The model of best fit was selected through backward stepwise regression and the model with the best balance between lowest AIC and highest adjusted [R-squared] was selected for modeling. Covariates for Vancouver were subsequently forecasted from historic climatological data from Vancouver. The forecasted values for covariates from Vancouver were then fit to the multiple linear regression model and fitted values yielded forecasted bloom dates for Vancouver.

As a second method, a vector autoregressive (VAR) model was fit to historic data from Washington, Kyoto, and Liestal. PBD for Washington, Kyoto, and Liestal were treated as the endogenous variables in the model and so the model was a $K=3$ dimensional VAR. Forecasted peak bloom dates for each of the three cities was extrapolated from the model. We then took the average of the peak bloom days over forecasted values for the three cities as our prediction for the peak bloom dates in Vancouver to 2032.

Statistical analysis was performed in R, version 4.1.2 (11-01-2021), “Bird Hippie.”

Results

For three locations with historical peak bloom dates data available, October 1st was found as the optimal dormancy initiation date and Table 2 summarizes the optimal parameters found. These parameters were subsequently used to calculate heating days, and chill days from historic temperature data.

Location	Tc (°C)	Rc (chill days)	Rh (anti-chill days)
Kyoto	6	-125	235
Liestal-Weideli	5	-68	210.5
Washington, D.C.	5	-13.5	264.6

Table 2. Estimated Parameters for the Cherry Blossoms per the Phenology Model

Coefficients and standard errors for multiple linear regression models fit to Kyoto, Washington, and Liestal are shown in Tables 3, 4, and 5 respectively. Forecasting results from extrapolation of these models are shown in Table 6. As can be seen from Table 3, GDD was highly significant to predicting peak bloom times in Kyoto. Average temperature also had a p-value less than 0.05. The model shows some signs of underfitting. Unfortunately, the data available for Kyoto was limited.

The model for Washington, DC is a much more developed model. GDD was still the most significant predictor by far for predicting peak bloom day. But several other predictors were also significant to the model at the 95% confidence level. Average temperature was significant at the 0.01 level. Sea level pressure, wind speed, cumulative precipitation, and absolute temperature difference were all significant at the 0.05 level. These covariates match more closely with our expectations from research that has been done on the topic previously. The ample availability and quality of the data for this site allowed us to build a fuller, better fitting model that explains more of the variance we see in peak bloom dates.

Table 3. Multiple Linear Regression Model: Kyoto, Japan

	β	s.e.	t	p	
(Intercept)	219.44	172.028	1.28	0.207	
Avg. Temperature	-0.01	0.003	-2.51	0.015	*
Chill days	0.02	0.011	1.95	0.056	
GDD	4.25	0.171	24.80	<2e-16	***
Total hrs. sunlight	-0.01	0.004	-1.74	0.087	
SLP (Jan-Mar)	-2.00	1.681	-1.19	0.238	
AIC	230.8				
Adj. R	0.917				

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Table 4. Multiple Linear Regression Model: Washington, DC

	β	s.e.	t	p	
(Intercept)	442.30	2084.000	0.21	0.833	
SLP	-3.38	1.614	-2.10	0.043	*
Cum. precipitation	0.01	0.004	2.13	0.039	*
Wind speed	-0.95	0.395	-2.42	0.021	*
Avg. temperature	-0.01	0.003	-3.09	0.004	**
Abs Temperature Diff	0.12	0.054	2.22	0.032	*
Chill days	-0.04	0.020	-2.00	0.052	
GDD	4.36	0.344	12.68	0.000	***
Sunlight (Jan-Mar)	18.05	59.670	0.30	0.764	
Sunlight (May-Sep)	-20.24	107.900	-0.19	0.852	
AIC	201.3				
Adj. R	0.931				

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

The linear regression model for Liestal undersmooths the data as can be seen from Table 5. Only GDD and average hours of summer sunlight are significant in this model. GDD is highly significant at the 0.001 level. Average sunlight hours is significant at the 0.01 level.

Tables 7, 8, and 9 show the coefficients and standard errors for the multiple linear regression models with SARIMA adjusted errors. For Kyoto, the model of best fit had 5 non-seasonal autoregressive lags, 4 non-seasonal moving average coefficients, 1 seasonal autoregressive lag and 2 seasonally adjusted moving average terms. The model showed seasonality with a period of 5 years. In Table 7, we note that the coefficient for GDD was considerably larger than its standard error and is therefore highly significant to the model. In fact, GDD dominates over all other covariates in the model. SLP is also significant in this model, but it is not as important to this model as is it for DC. We also observe that the 5th order lag is highly important for this model.

Table 5. Multiple Linear Regression Model: Liestal, Switzerland

	β	s.e	t	p	
(Intercept)	-798.70	273.100	-2.92	0.005	**
Sunlight (May-Sep)	54.77	18.650	2.94	0.005	**
Abs temperature diff	0.02	0.012	1.38	0.173	
GDD	4.47	0.064	70.34	<2.00E-16	***
Avg. temperature	0.00	0.001	-1.54	0.128	
Chill days	0.01	0.007	1.29	0.202	
AIC	162.6				
Adj. R	0.996				

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Table 7. Coefficients for Multiple Linear Regression Model with SARIMA Adjusted Errors for Cherry Blossom Peak Bloom: Kyoto, Japan

Model:	SARIMA (5,0,4) (1,0,2) [5]	
	β	s.e.
AR1	0.324	0.077
AR2	-0.424	0.075
AR3	-0.331	0.075
AR4	0.352	0.066
AR5	-0.865	0.074
MA1	0.164	0.144
MA2	1.243	0.179
MA3	-0.133	0.169
MA4	0.427	0.160
SAR1	0.327	0.138
SMA1	1.191	0.158
SMA2	1.000	0.166
Intercept	427.477	17.613
Drift	-0.027	Inf
Avg. Temperature	-0.003	0.001
Chill Days	0.044	0.003
GDD	3.737	0.029
Total Sunlight Hrs. (Jan-Mar)	-0.007	0.001
SLP (Jan-Mar)	-3.975	0.186
σ^2	0.3817	
AIC	186.58	
BIC	231.26	
Log lik	-73.29	
RMSE	0.5229	
MAPE	0.4424	

The model for Washington, DC is quite similar and has 6 non-seasonal and 3 seasonal autoregressive terms, and 4 non-seasonal and 5 seasonal moving average terms. As can be seen from Table 8, the coefficients for GDD, wind speed, and SLP were therefore highly significant to predicting peak bloom day. It is unfortunate that data for wind speed and SLP were not available for all sites as it would have been interesting to see whether these covariates are similarly significant in other locations. As for the SARIMA coefficients, it is clear that the seasonally adjusted autoregressive terms, particularly SAR2, SAR4, and SAR5, are highly important to the model's predictive power. As with Kyoto, we observe a 5-year seasonal cycle with peak bloom day in DC. The model for Liestal differs from the other two sites.

Table 8. Coefficients for Multiple Linear Regression Model with SARIMA Adjusted Errors for Cherry Blossom Peak Bloom: Washington, DC

Model:	SARIMA (6, 0, 4) (3, 0, 5) [5]	
	β	s.e.
AR1	-1.765	Inf
AR1	-1.331	Inf
AR1	-1.384	0.068
AR1	-1.841	Inf
AR1	-1.223	Inf
AR1	-0.392	0.090
AR1	1.060	0.108
AR1	1.030	0.091
AR1	0.826	0.119
AR1	-0.136	0.079
AR1	-1.241	0.013
AR1	-0.923	0.007
AR1	-0.153	0.012
AR1	-0.925	0.007
AR1	-1.241	0.013
AR1	-0.999	Inf
AR1	0.930	Inf
AR1	-0.691	Inf
AR1	-0.674	Inf
Intercept	4842.508	Inf
Drift	0.034	0.001
SLP (Jan-PBD)	-6.635	0.043
Cum. Precipitation	0.015	Inf
Wind Speed	-0.983	0.004
Avg. Temperature	-0.011	Inf
Mean Absolute Temp Diff (*0.1)	0.081	0.002
Chill Days	0.006	0.001
GDD	4.264	0.019
Avg. Hrs. Sunlight (Jan-Mar)	-97.944	Inf
Avg. Hrs. Sunlight (May-Sep)	-221.542	Inf
sigma^2	0.0017	
AIC	94.28	
BIC	152.92	
Log lik	-16.14	
RMSE	0.0257	
MAPE	0.0228	

The model for Liestal has 1 non-seasonal and 2 seasonal autoregressive lags, and 0 non-seasonal and 5 seasonal moving average coefficients. The period for seasonality is only 1 year but the model coefficients and fit differ from a non-seasonal ARMA(3, 5) model. GDD dominates over all other covariates in this model and the seasonally adjusted autoregressive order 2 lag is highly significant.

Table 9. Coefficients for Multiple Linear Regression Model with SARIMA Adjusted Errors for Cherry Blossom Peak Bloom: Liestal, Switzerland

Model:	SARIMA (1, 0, 0) (2, 0, 5) [1]	
	β	s.e.
AR1	0.323	0.172
SAR1	-0.374	0.016
SAR2	-1.000	0.004
SMA1	-0.198	0.230
SMA2	1.081	0.958
SMA3	-1.173	0.477
SMA4	0.021	0.968
SMA5	-0.723	0.681
Intercept	-930.457	199.144
Avg. Hrs. Sunlight (May-Sep)	63.711	13.546
Mean Absolute Temp Diff (*0.1)	0.002	0.013
GDD	4.533	0.073
Avg. Temperature	-0.001	0.002
Chill Days	0.011	0.005
sigma^2	0.3848	
Log lik	-60.14	
AIC	150.27	
BIC	183.56	
RMSE	0.5506	
MAPE	0.4049	

Table 10 shows a comparison of the predictive power of the linear models and the linear models with SARIMA adjusted errors and shows the root mean squared error (RMSE) of the actual peak bloom dates compared to the PBDs predicted by the model. The RMSE is much lower for the SARIMA adjusted models, indicating that these models have a much better fit to the historical data. We argue that the SARIMA adjusted models give more accurate forecasts due to the fact that these models are able to detect seasonal trends whereas simple linear models are not. Global weather patterns such as El Niño are well known to occur cyclically with quasi-predictive seasonality. We believe that modeling bloom dates—which are closely tied to cumulative heating and cooling temperatures—are likely to behave with quasi-regular seasonality as well.

Table 10. Comparison of Predictive Power with Linear Regression Model and Linear Regression Model with SARIMA Adjusted Errors

	RMSE Linear Model	RMSE SARIMA Model
Kyoto		0.5229
Liestal	0.7462	0.5506
Washington	1.5085	0.0257

Forecasts for the day of peak bloom from linear regression models with SARIMA adjusted errors are shown in Table 11. Forecasts from the VAR model are shown in Table 12.

Table 11. Forecasts for Cherry Blossom Peak Bloom (2022-2032): Linear Regression Model

Year	Washington, DC	Kyoto, Japan	Liestal, Switzerland	Vancouver, BC
2022	98.3	97.2	114.7	91.6
2023	93.4	99.3	116.9	90.0
2024	93.4	94.2	117.3	89.2
2025	89.8	98.8	84.5	86.9
2026	89.3	100.5	114.4	88.5
2027	107.8	97.5	91.4	90.4
2028	94.2	91.0	94.3	90.2
2029	93.9	93.5	79.0	88.2
2030	96.9	98.0	116.8	88.9
2031	97.3	103.4	114.3	87.5
2032	101.8	99.8	107.4	88.5

Table 12. Forecasts for Cherry Blossom Peak Bloom (2022-2032): VAR Model

Year	Kyoto, Japan	Washington, DC	Liestal, Switzerland	Vancouver, BC
2022	94.5	90.0	91.7	92.0
2023	95.0	92.1	99.5	95.5
2024	96.0	92.7	100.7	96.5
2025	96.2	93.0	101.5	96.9
2026	96.3	93.1	101.8	97.0
2027	96.3	93.1	101.9	97.1
2028	96.4	93.1	101.9	97.1
2029	96.4	93.1	101.9	97.1
2030	96.4	93.1	101.9	97.1
2031	96.4	93.1	101.9	97.1
2032	96.4	93.1	101.9	97.1

Discussion

Conclusion

References

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