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Assessing the factors affecting maple syrup yield in the US and predicting production potential in Kentucky

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ABSTRACT

Maple syrup is an important part of the economy in various regions of the United States. Studies on maple syrup production potential mostly use climatic factors as determinants and, therefore, fail to account for non-climatic factors. In this study, we applied a stochastic production function framework to establish a relationship between maple syrup yield and a set of climatic (temperature and tapping season length) and non-climatic determining factors, such as the number of maple trees and utilization rate of the potential number of taps. Tree characteristics, climatic, and other factors had mixed effects on syrup yield. The number of maple trees, the number of taps, and the minimum temperature had marginal negative effects on average syrup yield, while the length of the season and the maximum temperature had positive effects. A predictive model was developed and used to estimate the potential production of maple syrup under low, medium and high utilization levels in Kentucky, a likely region for maple syrup production. This model could be useful for maple syrup research, education, and extension in maple-producing states.

1. Introduction

Maple syrup derived from maple tree sap has a long history as an important agroforestry product in North America (Koelling et al., 1996; Houle et al., 2015; Snyder et al., 2018, 2019; Rapp et al., 2019). On land ownerships with accessible maple trees in the northern United States, maple sap is collected and processed into syrup and sugar and is an integral part of the winter/spring farm experience (Ramsingh, 2018). Historically, farmers drilled holes, inserted spouts into the trees (a process called tapping) and collected the sap in buckets (Heiligmann et al., 2006). Many still use this classic technique, although in modern operations tubing (plastic tubes) is used to deliver the sap to a centralized processing point rather than collecting it in individual buckets (Legault et al., 2019). After sap collection, producers boil the sap, evaporating much of the excess water until a desired sugar content is achieved at which point the solution is considered maple syrup.

Maple syrup yield is influenced by various factors (Duchesne et al., 2009), including number of maple trees and taps (Perkins and Berg, 2009; Farrell and Chabot, 2012), temperature (Rapp and Crone, 2015; Legault et al., 2019), tapping season length (Rapp et al., 2019), and technological advancements (Duchesne and Houle, 2014). The majority of maple syrup production is derived from two species: sugar maple (*Acer saccharum* Marsh.) and red maple (*Acer rubrum* L.) (Whitney and Upmeyer, 2004; Heiligmann et al., 2006; Farrell and Stedman, 2013; Frey et al., 2023). Diurnal temperature trends are a foundational factor in maple syrup production, with freezing nights and thawing days stimulating sap flow (Marvin, 1967; Legault et al., 2019). The tapping season length affects the timing and amount of freeze/thaw cycle, number of sap collection days, and the total sap volume collected (Rapp et al., 2019). Technological advancements like reverse osmosis, which uses a semipermeable membrane to separate about 60 % of water from maple sap before boiling, and vacuum tubing, where a vacuum system line is installed to draw the sap from the tree to the collection tank through a tubing system, have enabled producers to tap more trees and

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increase sap processing efficiency, thereby augmenting production potential (Duchesne and Houle, 2014). Understanding these factors that influence syrup yield is essential for assessing its production potential and the development of the maple syrup industry.

There is a well-established and predictable relationship between alternating freezing and thawing temperatures to sap flow (Tyree and Zimmerman, 2002; Cirelli et al., 2008; Skinner et al., 2010). Studies have also examined climate's influence on maple syrup production (Duchesne et al., 2009; Houle et al., 2015; Rapp et al., 2019). Existing studies have often focused on single factors, at the exclusion of other non-climatic factors affecting maple syrup production levels. The consideration of the interplay of biological, social, and economic factors in maple syrup production could help in assessing the full potential of maple syrup production. By considering these interacting factors, it is possible to develop a predictive model which calculates the maple syrup production potential of a region and hence identifies the potential areas for maple syrup production. In recent years, there has been increasing interest in expanding maple syrup production to regions other than traditional Northeastern states, including Kentucky (KMS, 2023; Hackworth et al., 2024). In North America, while maple syrup production is typically associated with regions in the northern United States and Canada, Kentucky in the southern region has also emerged as a potential maple syrup producer due to its large inventory of native maple trees and its above- and below-freezing temperature between January to March (Green, 2012). The potential for maple syrup production in Kentucky has been unexplored, and therefore this research aims to address this gap by investigating maple syrup production potential in Kentucky.

This study also fills a gap in the literature on maple syrup production by moving beyond the prevalent univariate approach and presenting a comprehensive multivariate analysis that examines the interactive effects of multiple factors on maple syrup yield. Specifically, our study considered the effects of temperature, number of maple trees, number of taps, and season length on syrup production in a given region. This study develops a "Multivariate Predictive Maple Syrup Production Model" using available county-level data from 13 maple syrup-producing states of the United States. The model aided in predicting maple syrup yield in regions like Kentucky that have maple trees, climatic conditions, and potential producers. Research outcomes from this study generated evidence-based information that could inform sustainable management of natural resource base (*Acer* spp.) and shows how climate (temperature) affects maple syrup production among other non-climatic factors. This information could be useful for county Extension agents and natural resource professionals because it will help them provide targeted education and Extension services to increase syrup production among landowners and aspiring current producers.

2. Methodology

2.1. Analytical framework

This study developed two models using the Just and Pope stochastic production function (Just and Pope, 1978; 1979) for maple syrup production. The first model included the maple syrup yield per tap as the dependent variable and a range of explanatory variables (Eq. (1)). This model aimed to provide a thorough overview of how the factors of interest structure regional maple syrup yield. The second model also used maple syrup yield per tap as the dependent variable and the set of explanatory variables identical to those in the first model but excluded the quadratic terms, interaction terms, time trend, and state indicator variables (Eq. (2)). The novelty of Eq. (1) lies in its specific application to maple syrup production, incorporating both linear and non-linear relationships that are tailored to the context of this industry. This model provides a more comprehensive framework for understanding the dynamics of syrup yield, based on the established econometric framework of the original Just and Pope model. Eq. (2) is indeed a reduced form of Eq. (1), excluding the quadratic and interaction terms. The primary motivation for including Eq. (2) is to evaluate the robustness and simplicity of our results. Furthermore, Eq. (2) serves as a baseline model that simplifies the interpretation of results. By comparing it to Eq. (1), we can better understand the incremental value that the additional terms (quadratic and interaction terms) bring to the analysis. The second model is needed to extend syrup yield prediction to a state where existing data is not available and must be a "reduced model" (one that contains a subset of potential predictors) so it can be extended to this new location like Kentucky (i.e., using the state indicator is not possible). The coefficients estimated from the second model were then used to develop a predictive model for maple syrup yield. In practical terms, model 2 may be used for forecasting and policymaking where simplicity and ease of interpretation are preferred while model 1, with its detailed specification, provides a deeper understanding of the factors influencing syrup yield, which can be useful for detailed analysis and understanding the underlying mechanisms.

Model 1 general equation:

$$\begin{aligned} Maple\ syrup\ yield = f\Big(&Number\ of\ maple\ trees_{it},\ (Number\ of\ maple\ trees_{it})^2,\ Number\ of\ taps_{it},\\ &(Numberoftaps_{it})^2, Numberofmapletrees_{it}xNumberoftaps_{it}, Averageseasonlength_{it},\\ &(Averageseasonlength_{it})^2, Meanminimumtemperature_{it}, (Meanminimumtemperature_{it})^2,\\ &MeanminimumtemperatureCV_{it}, Meanmaximumtemperature_{it}, (Meanmaximumtemperature_{it})^2,\\ &MeanmaximumtemperatureCV_{it}, Meanminimumtemperature_{it}xMean\\ &maximumtemperature_{it}, Timetrend_t, Statedummies_i) \end{aligned} \tag{1}$$

Model 2 general equation:

$$\begin{aligned} Maplesyrupyield = f(&Numberofmapletrees_{it}, Numberoftaps_{it}, Averageseasonlength_{it},\\ &Meanminimumtemperature_{it}, Meanmaximumtemperature_{it}) \end{aligned} \tag{2}$$

In these equations, the subscript i represents the region, and t represents the year.

2.2. Study area and dataset

The 13 States in the Northeastern United States are known for maple

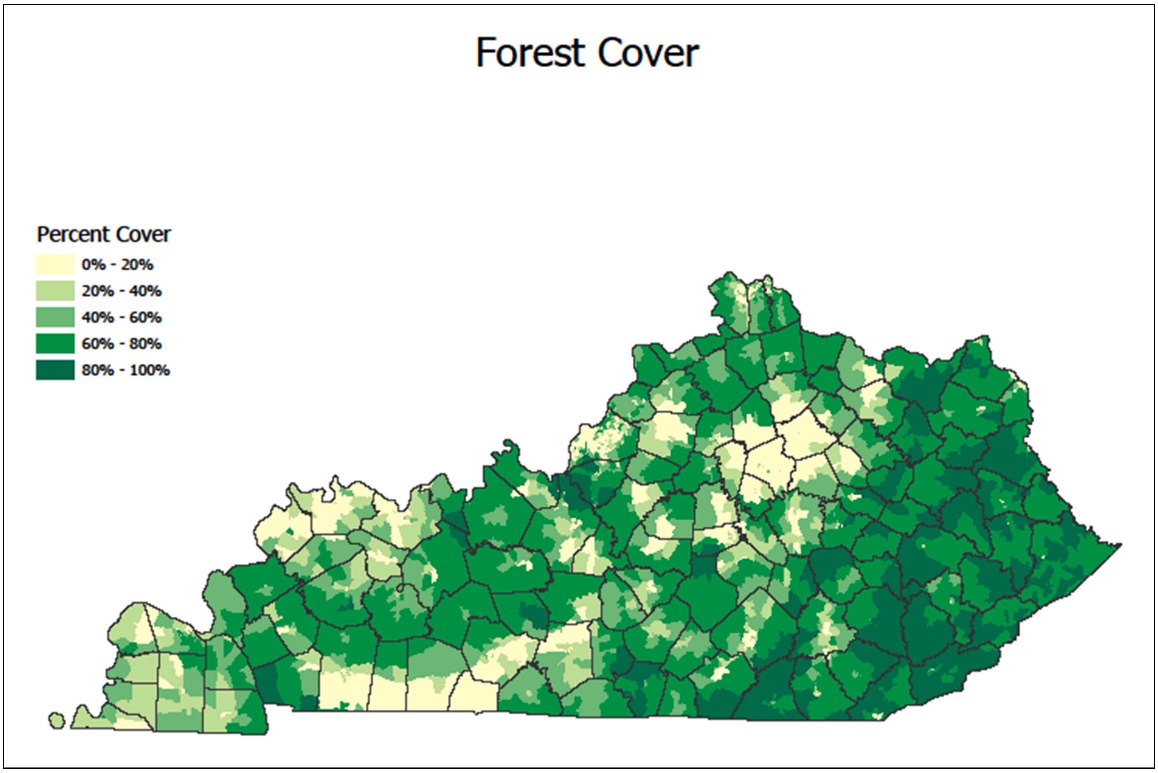

Fig. 1. Map of Kentucky, USA showing forest cover (Source: Kentucky Forest Action Plan., 2020).

syrup production. These states include Connecticut (CT), Indiana (IN), Maine (ME), Massachusetts (MA), Michigan (MI), Minnesota (MN), New Hampshire (NH), New York (NY), Ohio (OH), Pennsylvania (PA), Vermont (VT), West Virginia (WV) and Wisconsin (WI). We used the data from these state counties to establish a relationship between variables and predict maple syrup production for other potential regions (Kentucky in our case). Kentucky is a state located in the southeastern region of the United States. It has an area of 104,659 square kilometers (40,409 square miles) and a population of 4.5 million people (U.S. CB, 2020). The GDP of Kentucky was $203.3 billion in 2019 (U.S. BEA, 2020). The unemployment rate in Kentucky is about 3.8 % (U.S. BLS, 2023). Major industries in Kentucky include manufacturing, agriculture, and tourism (KCED, 2020). Kentucky has an estimated 50,464.3 square kilometers (12.4 million acres) of forest, and the dominant tree species groups include oak (*Quercus* spp.), hickory (*Carya* spp.), and maple (*Acer* Spp.) (USDA FS, 2023). The climate in Kentucky is humid subtropical, averaging around 2 °C (mid-30s °F in the winter and 30 °C (mid-80s °F) in the summer (NWS, 2020). Fig. 1 shows the map of Kentucky with forest cover across the state.

Maple syrup panel data were obtained from the USDA NASS Maple Syrup Crop Annual Reports, which collect information through an annual survey of maple syrup producers on the number of taps, production, season length, price, and sales of maple syrup by state and county. The reports cover multiple states across time and state counties and are publicly available. Before 2016, the reports focused on Northeastern states, covering only 11 states (CT, ME, MA, NH, VT, NY, OH, MI, MN, PA, and WI). Indiana and West Virginia were added in 2016. In 2019, five states (CT, IN, MA, MN, WV, and OH) were removed from NASS annual reports because they could not meet the reporting threshold.

Data on the maple tree inventory by state were obtained from the FIA database (USDA FS, 2021). The query on FIA EVALIDator (online tool) retrieves the average number of trees per acre of chosen maple species (red and sugar) by county, inventory year, and diameter class. To obtain the total number of maple trees in a county, we multiplied the average trees per acre by the forestland acreage in that county for the corresponding inventory year.

Temperature data were obtained from PRISM weather and climate data (PRISM, 2021), hosted at Oregon State University.[1] The PRISM Climate Group employs comprehensive monitoring networks to gather climate data and implements stringent quality control procedures to generate spatial climate datasets that reveal climate trends over different periods. These datasets are created using diverse modeling techniques and are available in various spatial and temporal resolutions, encompassing the period from 1895 to the present day. Among these datasets is one that presents detailed temperature data, with each record featuring a site ID, longitude, latitude, elevation, and pentad values (for every 5 days) starting on January 1st.

2.2.1. Dependent variable

The dependent variable for the analysis was the maple syrup yield per tap in gallons (1 gallon = approximately 3.785 liters) for sugar and red maple trees. The data from 2001 to 2018 were obtained from the USDA NASS annual reports for maple production (USDA NASS, 2018). The use of the data within this period was contingent upon the availability of all the data necessary for our analysis by the time we started this study. In the reports, yield data were available from 2001 to 2018 for CT, ME, MA, MI, NH, NY, OH, PA, VT, and WI. Similarly, yield data were available from 2016 to 2018 for IN, MN, and WV. NASS only tracks annual data at the state level, so the numbers apply to all counties within those states.

2.2.2. Explanatory variables

The explanatory variables were divided into four major categories: maple tree characteristics, climatic characteristics, time trend, and state dummy variables.

[1] PRISM provides daily time series temperature data for individual locations (by county and by specifying coordinates of latitudes and longitudes).

2.2.2.1. Maple tree characteristics. Data on number and size of maple trees (sugar and red) greater than or equal to 33 cm (13 inches) diameter at breast height (DBH) for all states were obtained from the FIA database (USDA FS, 2021). This DBH considers that the maple trees are big enough to tap. The number of taps was obtained from USDA NASS annual maple reports. Data on number of taps were available for the years 2002, 2007, 2012, and 2017 (NASS 5-year census data). For 2001 and 2018, the data was assumed to be the same as the closest year (2002 and 2017 respectively). For the other missing years, the data was assumed to be the same as the data from prior available years (2003–2006 was assumed to be the same as 2002, 2008–2011 was assumed to be the same as 2007, and 2013–2016 was assumed to be the same as 2012).

2.2.2.2. Climatic characteristics. Climatic characteristics included the average maximum temperature, average minimum temperature, and average season length for tapping maple trees. The pentad (value for every five days) temperature data were obtained from the PRISM weather and climate data (PRISM, 2021). The temperature data range for each state was filtered according to the tapping season length from NASS maple reports. Generally, these months range from January to May. The exact timing of the tapping season varies from state to state and is driven by the presence of daily temperature cycles whose frequency is largely determined by latitude. Average season length was obtained from NASS maple reports, which were available from 2013 to 2018 for most of the states. The average season length for 2001–2012 was estimated by using the available data from 2013 to 2018. For example, the average minimum temperature during maple sap flow days from 2013 to 2018 for Albany County, New York was calculated as -10.43 °C. All temperatures less than or equal to this value were then multiplied by five to convert it to a value corresponding to pentad data to obtain the season length for the given period (2001–2012) for Albany County.

2.2.2.3. Time trend. The time trend variable was also added to represent the effect of technological progress (Ochuodho et al., 2013; 2014), such as improved tapping practices, during the study period. We assumed that the time trend variable, which is an index of years of data, would reflect any technological improvements in maple syrup production (Perkins et al., 2015) and, thus, we anticipated that it would have a positive effect on syrup yield (Ochuodho et al., 2013; 2014).

2.2.2.4. State indicator variables. State indicators were included to act as a control for any variables that were not included in the study, as well as to account for any characteristics that did not change over time that could be related to the outcome of the study (Garavaglia and Sharma, 1998; Gujarati, 2022). This helped to reduce the potential for bias due to omitted variables (Kato et al., 2011). State indicator variables were used to represent the 13 states acting as subgroups of our study; Wisconsin was selected as the baseline case. Table 1 provides the descriptive statistics of the variables used in this study.

In *Model 1*, quadratic terms and interaction terms were also included for regression analysis. We included quadratic terms of total trees, number of taps, average season length, mean minimum temperature, and mean maximum temperature to account for any nonlinear relationships between them and syrup yield. Additionally, we included interaction terms (trees x number of taps, mean minimum temperature x mean maximum temperature) to capture possible joint impacts. This was done similarly to Cabas et al. (2010) and Ochuodho et al. (2014).

2.3. Data analysis

2.3.1. Regional model

We used the Just and Pope (1978, 1979) stochastic production function framework to analyze how factors influencing yield/output can affect both the mean of yield/output. This model, as described by Gujarati (2003), breaks down the production function into a deterministic component related to output level and a stochastic component related to output variability and then estimates the effects of explanatory variables on both expected output and its variance. The general form of the Just and Pope Production function is:

$$Y = f(V, \beta) + \mu = f(V, \beta) + \phi(V, \theta)^{0.5}\varepsilon \tag{3}$$

Where Y is syrup yield, V is a vector of explanatory variables and $f(.)$ is the mean function (or deterministic component of production) relating V to average yield with β as the associated vector of estimated parameters. μ is a heteroscedastic disturbance term with a mean of zero. $\Phi\ (V, \theta)$ is the variance function (or stochastic component of output) that relates V to the standard deviation of yield with θ as the corresponding vector of estimated parameters, and ε is a random error with zero mean and variance σ^2. With this formulation, independent variables (factors) such as mean maximum and minimum temperatures can independently influence the mean yield of syrup ($E[Y] = f\ [V, \beta]$) and yield variance ($Var[Y] = Var[\mu] = \phi\ [V, \theta]\ \sigma^2$).

This study has a relatively large sample,[2] so the three-stage feasible generalized least squares (FGLS) under the heteroscedastic disturbances estimation procedure (Judge et al., 1985; Saha et al., 1997) is an appropriate choice. This was implemented using STATA statistical software, following the methods of Ochuodho et al. (2013) and Ochuodho et al. (2014).

The first stage of the FGLS estimation technique uses ordinary least squares (OLS) to regress Y *on* $f\ (V,\ \beta)$ with the least-squares residuals $\widehat{\mu}(\widehat{\mu} = y - f(V, \widehat{\beta}))$ as a consistent estimator of heteroscedastic disturbance term (μ). Although the resulting variance (σ^2) is unobservable, the second stage uses the first stage's least square residuals to estimate the marginal impacts of explanatory variables on production variance (θ). The second step predicts the residuals and builds squared residuals ($\widehat{\mu}^2$), which are then regressed on its asymptotic expectation $\varphi\ (V,\ \theta)$ with $\varphi()$ assumed to be an exponential function, $\ln\sigma_i^2 = Z_i'\theta$. The squared residuals (the projected error terms from the second stage) were used as weights in the third/final stage to provide FGLS estimations for the mean yield equation. Under a wide range of conditions, the resulting estimate of β in this final step is consistent and asymptotically efficient, and the entire process corrects for the heteroscedastic disturbance term (Just and Pope, 1978).

A fixed-effects model, which controls for omitted variables that differ between states but are constant over time, or a random-effects model, which considers that some omitted variables may be constant over time but vary between cases, can be used to estimate the panel data (described in more detail below). To establish which approach should be utilized, a Hausman specification test was performed. The null hypothesis of no association between state-specific effects and explanatory variables was rejected as a result of the analysis (**Supplementary Table 1**), and the maple syrup yield equations were regressed using a fixed-effects model with state indicator variables per the approaches of Cabas et al. (2010) and Ochuodho et al. (2013).

2.3.1.1. Heteroscedasticity, stationarity and endogeneity tests. Panel data is a type of empirical data that tracks a specific set of entities or people over several time points (Eric, 2019). Endogeneity, heteroscedasticity, and stationarity are characteristics of panel data that may have an impact on the analytical findings (Wooldridge, 2010). Panel data exhibit heteroscedasticity, which is characterized by the fact that the variance of the error term varies across observations (Wooldridge, 2010). In the

[2] Over 18 years of data in 13 states by county [CT (8), IN (92), ME (16), MA (14), MI (85), MN (87), NH (10), NY (62), OH (88), PA (67), VT (14), WV (54), and WI (72)] include number of taps, syrup yield per tap, average season length, mean min/max temperatures and number of tappable maple trees.

Table 1
Descriptive statistics of dependent and explanatory variables used in a predictive model.

Variables	Observations	Mean	Standard Deviation	Minimum	Maximum
Dependent variable Syrup yield (gallons/tap)	8514	0.22	0.06	0.097	0.39
Explanatory variables					
Maple trees					
Total trees (≥ 33 cm DBH)	7259	2.77e+07	9.31e+07	0	1.56e+09
Number of taps	5436	31,466.25	11,6454.4	8	2099,849
Climatic					
Average season length (n)	8478	30.7	12.07	0	70
Mean Maximum Temperature (°C)	8440	7.19	2.4	-1.1	14.42
Mean Minimum Temperature (°C)	8457	-3.91	2.72	-15.06	3.33

STATA, Breusch–Pagan/Cook–Weisberg test for heteroscedasticity (**Supplementary Table 2**) rejected the null hypothesis of constant variance (p-value < 0.01) and confirmed the presence of heteroscedasticity. The fact that the mean and variance of a variable stay constant over time is known as stationarity and it is a property of panel data. We employed a Fisher-type unit-root test based on augmented Dickey-Fuller tests to ensure that the data used were stationary (Choi, 2001). Panel data stationarity was confirmed using inverse chi-square and other statistics (**Supplementary Table 3**). Serial correlation or autocorrelation, which denotes a non-zero correlation between variables at different time intervals, is typically only defined for weakly stationary processes (Taylor, 2018). Panel data exhibit endogeneity when the independent variables are correlated with the error term, which leads to inaccurate estimates of the regression coefficients (Wooldridge, 2010). Most of the explanatory variables in this study (such as the number of trees and taps, for example) were likely to be endogenous to county-level maple production decisions. We used the Durbin–Wu–Hausman test to guarantee there was no reverse causality in the estimations, which could bias the results (Kato et al., 2011). The test revealed a large p-value (**Supplementary Table 2**) failing to reject the null hypothesis of variables being exogenous. The presence of endogeneity can be rectified by variance-weighted two-stage least squares (VW2SLS) estimation (Wooldridge, 2009). Our models were estimated using VW2SLS, which also corrects for heteroscedasticity.

2.3.2. Model validation

Model validation for panel data analysis was used to ensure that a statistical model is accurate (Smith and Rose, 1995; Grant 2021). It entails comparing the model's estimated outputs against observed or real values to evaluate how well they match. This is crucial because it ensures that the model accurately captures the underlying relationships in data and may be used to inform decision-making based on the results. There are different statistical metrics to validate a predictive model. Such metrics are coefficient of determination (R^2), bias, mean absolute error (MAE), root mean square error (RMSE), and some other cross-validation procedures (Aspexit, 2019). When calibrating and validating a model, the goodness-of-fit of the model is often assessed by comparing predicted and observed values (Smith and Rose, 1995). We used the actual (reported) data and predicted data for the validation of our model. This is based on the calculation of the coefficient of determination (R^2). R^2 indicates the amount of variance in the observed values that can be attributed to the variation in the predicted values, while the slope and the intercept describe the consistency and the model bias, respectively. This value of R^2 ranges from 0 to 1, with a higher value indicating a smaller difference between the predicted and observed data (Frost, 2017). Smith and Rose (1995), Mesplé et al. (1996), and Piñeiro et al. (2008) have all discussed this concept in detail. For our validation, we separated our data into the training set (set of data used to create a model) and testing set (set of validation data that you use to compare your model's accuracy) (Grant, 2021). Using the training set (data from 2001 to 2015), we developed a model for validation. We used the model (data from 2001 to 2015) and testing (data from 2016 to 2018) datasets to predict the maple production potential. The R^2 value for the predicted vs reported maple production data was found to be 0.981 (**Supplementary Table 4**).

2.3.3. Extending maple syrup yield potentials to Kentucky

We conducted variance-weighted least squares regression in STATA to determine the relationship between yield per tap and the primary factors that influence syrup yield, namely the total number of maple trees (sugar and red) greater than or equal to 33 cm (13 inches) DBH, the number of taps, average season length (in days), and the mean of maximum and minimum temperatures (in °C). These are important natural factors that influence the flow of sap, which eventually becomes maple syrup. Once the production function relationship between syrup yield per tap and the independent variables was established as model two, we fitted the empirical data for each county in Kentucky into the model to estimate the potential syrup production for each Kentucky County using the estimated model coefficients. As NASS does not report maple statistics for Kentucky, the variables considered for the Kentucky maple syrup production calculation were obtained from various sources. The FIA database provided the total number of sugar and red maple trees, while temperature data were obtained from the PRISM climate group. The season length was computed as the average of the neighboring states of Kentucky (Ohio and West Virginia). The number of taps (100 %, 50 %, and 25 %) was calculated based on the utilization rate of Vermont,[3] which is the largest maple syrup producer in the United States. Our study aimed at predicting Kentucky's maple syrup potential incorporated Vermont's utilization rates of 1.44 %, 0.72 %, and 0.36 % (our calculation based on NASS-reported number of taps against maple trees inventory) to assess high, medium, and low production levels, respectively. These three distinct production levels were used to reflect the diverse range of maple syrup production potentials in Kentucky. By considering various levels of utilization, we aim to provide a realistic projection of how syrup production might vary across the state under different conditions. This analysis helps producers understand the potential impacts of factors like weather patterns and maple tree inventories on production. Furthermore, examining these various production scenarios allows us to evaluate potential best practices and strategies for maximizing maple syrup output, supporting informed decision-making among maple syrup stakeholders in the region. With all the variables and the relationship established through model 2, we computed Kentucky's maple production potential as low, medium and high based on VUR for 2018.

[3] Utilization rate of each Vermont's counties in 2018 = NASS reported taps number divided by FIA total number of maple trees with DBH of at least 13". Vermont Utilization Rate (VUR) is the average of all counties and calculated to be 1.445 %. We used this rate to find the potential number of taps in the Kentucky state, which is considered 100 %. Then the 50 % and 25 % potential number of taps were calculated to be half and quarter of 100 % respectively.

Table 2
Regression results of mean syrup yield.

	Model 1: Factors effects on mean syrup yield per tap			
Explanatory variables	Coefficient	Standard error	z-stat	p-value
Intercept	-0.111	0.024	-4.68	0.000***
Maple tree characteristics				
Total trees	-5.76E-11	6.91E-12	-8.34	0.000***
(Total trees) ^{2}	3.45E-20	5.21E-21	6.61	0.000***
Number of taps	-2.57E-08	6.92E-09	-3.72	0.000***
(Number of taps) ^{2}	1.50E-14	4.82E-15	3.11	0.002***
Trees x no. of taps	1.08E-17	8.11E-18	1.33	0.183
Climatic characteristics				
Season length	0.004	0.0001	34.93	0.000***
(Season length) ^{2}	-0.00005	1.85E-06	-26.94	0.000***
Min. Temperature	-0.0408	0.004	-10.58	0.000***
(Min. Temperature) ^{2}	-0.0018	0.0002	-10.85	0.000***
Min. Temperature CV	-0.00003	8.66E-06	-3.5	0.000***
Max. Temperature	0.042	0.0044	9.38	0.000***
(Max. Temperature) ^{2}	-0.002	0.0002	-10.48	0.000***
Max. Temperature CV	-0.00002	0.00001	-1.07	0.286
MinTemp x MaxTemp	0.004	0.0004	10.71	0.000***
Time Trend	0.0071	0.00007	95.39	0.000***
State indicator variables				
Connecticut	-0.053	0.001	-36.86	0.000***
Indiana	-0.068	0.002	-40.28	0.000***
Maine	0.013	0.002	6.7	0.000***
Massachusetts	-0.044	0.001	-31.37	0.000***
Michigan	-0.014	0.001	-13.37	0.000***
Minnesota	-0.097	0.001	-74.43	0.000***
New Hampshire	-0.017	0.002	-10.76	0.000***
New York	-0.021	0.001	-20.83	0.000***
Ohio	-0.009	0.001	-6.55	0.000***
Pennsylvania	-0.045	0.001	-34.48	0.000***
Vermont	0.039	0.002	21.47	0.000***
West Virginia	-0.151	0.004	-39.69	0.000***

Note: Wisconsin was excluded from the regression to avoid a dummy variable trap (Gujarati, 2022). Statistical significance (***$p < 0.01$).

3. Results and discussion

3.1. Results

3.1.1. Maple syrup mean yield

In *Model 1*, most variables responsible for affecting the mean syrup yield were statistically significant (Table 2). We presented the result of each factor and their relation in affecting the mean syrup yield in the following headings.

3.1.1.1. Maple tree characteristics. The effect of the total number of maple trees (≥ 33 cm DBH) within a state was negative and statistically significant (p-value < 0.01). The quadratic term for total trees affected the yield positively (p-value < 0.01). A similar result was seen with the linear and quadratic terms of the number of taps. An interaction term between total trees and the number of taps was positive but not significant (p-value = 0.183).

3.1.1.2. Climatic characteristics. The average season length had a significant positive effect (p-value < 0.01) on the maple syrup yield. The effect of the quadratic term of average season length was negative and significant (p-value < 0.01). The interaction between the minimum and maximum temperatures had a significant positive (p-value < 0.01) effect on the mean syrup yield. Similarly, mean minimum and mean maximum temperatures were negatively and positively associated with syrup yield (p-value < 0.01) respectively, while their quadratic terms were negatively associated (p-value < 0.01). The effect of minimum temperature coefficient of variation (CV) is negative (p-value < 0.01), while the effect of maximum temperature CV is negative but not significant (p-value = 0.286).

3.1.1.3. Time trend. A significant positive (p-value < 0.01) effect on the maple syrup yield by the time trend variable was observed.

3.1.1.4. State indicator variables. State indicator variables showed that syrup yield varies significantly (p-value < 0.01) compared to Wisconsin. Vermont and Maine have positive coefficients, indicating higher mean syrup yield, while other states have negative coefficients indicating lower mean syrup yield than Wisconsin.

3.1.2. Production estimation for Kentucky

For model 2, the regression result (**Supplementary Table 5**) showed that the considered variables were statistically significant (p-value < 0.01). The following relationship was obtained from the analysis.

$$\begin{aligned} \textit{Syrup yield per tap} = {} & 0.2765618 - 4.47 * 10^{-11} \\ & * \textit{Total trees} (\geq 33cm\ DBH) + 4.29 \\ & * 10^{-08} * \textit{Number of taps} \\ & + 0.001109 * \textit{Average season length} \\ & + 0.0024038 * \textit{Mean of minimum temperature} \\ & - 0.010489 * \textit{Mean of maximum temperature} \end{aligned} \tag{4}$$

With the relationships established in Eq. (4), we calculated Kentucky's maple syrup production potential for 2018. The production potential was calculated for all counties (**Supplementary Information 6**). Based on our analysis, the potential maple syrup production levels in Kentucky were estimated to be approximately 348,236 liters (91,994 gallons) at low potential production level, 698,182 liters (184,440 gallons) at medium potential production level, and 1,403,199 liters (370,686) gallons at high potential production level.

The potential of maple syrup yield was distributed unevenly across Kentucky (Fig. 2) with high to medium potential on the eastern side of the state. The counties in the southeast region with high yield potential are Pike, Letcher, Perry, Harlan, Leslie, Bell, and Wayne. Lewis County in the northeast and Morgan County in the central northeast also show high potential. The central and western regions exhibit a low potential for maple syrup yield.

3.2. Discussion

The findings of this study from model 1 suggest that there is a negative linear effect between the total number of maple trees and syrup yield, indicating that as the number of maple trees (≥ 33 cm DBH) increases, the total syrup productivity decreases. This relationship can be attributed to the basic dynamics of forest stands, where an increase in the number of stems per acre results in a reduction in the average DBH, which decreases sap yield. We can infer that having fewer large trees in the stand yields more syrup volume than having a larger number of smaller DBH trees. This finding is in line with the study by Farrell and Stedman (2013), which identified the presence of many small maple trees as one of the obstacles that lower production. The quadratic term for total maple trees captures non-linear relationships between the total number of maple trees and maple syrup yield. The negative coefficient for the quadratic term suggests that as the total number of trees increases, the syrup yield initially increases at a decreasing rate, and then eventually starts decreasing. There is an optimal range for the number of trees per acre to maximize syrup yield, and going beyond this range can result in diminishing returns. The coefficient for the number of taps is negative and significant, indicating that an increase in the number of taps per tree reduces the syrup yield per tap. This result could be due to the physical damage caused to the tree during tapping, which reduces the tree's ability to produce sap. The results showed that the quadratic term for the number of taps had a positive effect on mean syrup yield. This suggests that up to a certain number of taps, adding more taps would increase the yield of syrup. However, beyond that point, adding more taps would result in a decrease in the syrup yield.

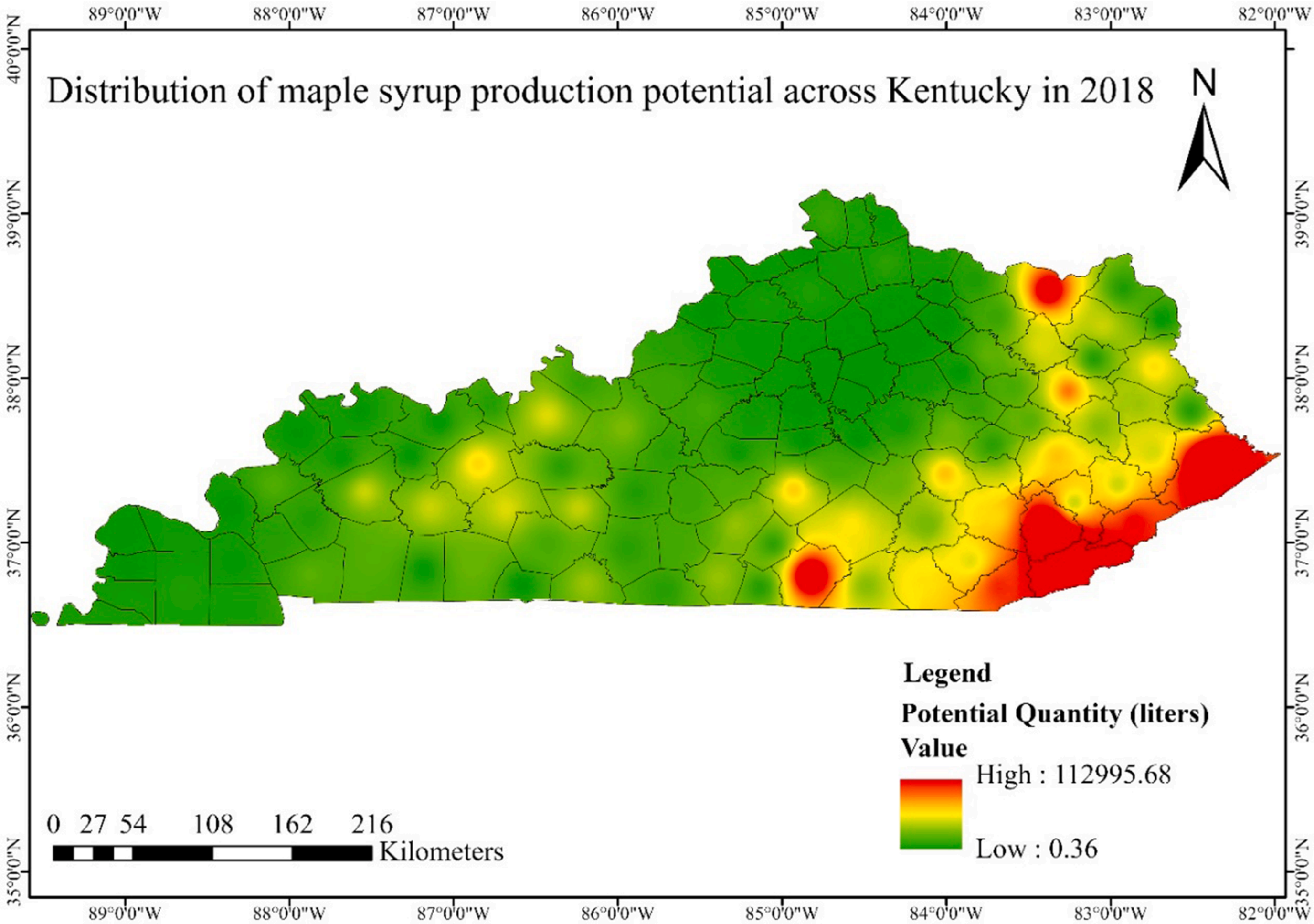

Fig. 2. Maple syrup yield potential by county in Kentucky in 2018 (Author-generated using ArcGIS 10.8.1).

The coefficient for average season length is positive and significant, indicating that a longer season length increases the syrup yield per tap. This result is consistent with the understanding that a longer season allows for more opportunities for freeze-thaw cycles which would increase sap production. The coefficient for the quadratic term of average season length is negative and significant, suggesting a nonlinear relationship between season length and syrup yield per tap. Specifically, the syrup yield per tap initially increases with season length but eventually reaches a maximum and then starts to decrease. In a study, it was found that the limited number of freezing nights and warm weather can cause tapholes to cease production prematurely, especially when collecting sap using buckets or gravity-based tubing (Farrell and Chabot, 2012). The coefficient for minimum temperature is negative and significant, indicating that a lower minimum temperature reduces the syrup yield per tap. This result could be because lower temperatures slow down the sap flow in the tree. The coefficient for a quadratic term of minimum temperature is also negative and significant, suggesting a nonlinear relationship between minimum temperature and syrup yield per tap. Specifically, the syrup yield per tap decreases at an increasing rate as the minimum temperature decreases. The coefficient for minimum temperature CV is negative and significant, indicating that greater variability in minimum temperature reduces the syrup yield per tap. This result could be because large fluctuations in temperature can stress the tree, affecting its ability to produce sap (Moran, 2022). The coefficient for maximum temperature is positive and significant, indicating that a higher maximum temperature increases the syrup yield per tap. This result could be because warmer temperatures increase the sap flow rate in the tree. The coefficient for a quadratic term of maximum temperature is negative and significant, suggesting a nonlinear relationship between maximum temperature and syrup yield per tap. Specifically, the syrup yield per tap initially increases with maximum temperature but eventually reaches a maximum and then starts to decrease. The coefficient for maximum temperature CV is not statistically significant, indicating that there is no significant impact of variability in maximum temperature on the syrup yield per tap. The coefficient for the interaction term between minimum and maximum temperature had a positive and statistically significant effect on the mean syrup yield. Previous studies (Duchesne et al., 2009; Houle et al., 2015) also reported the important relationship between the day and night temperatures necessary for sap to flow.

The positive and significant impact of the time trend on syrup yield demonstrated that advancements in technology have contributed to the increased yield of maple syrup. This is supported by the studies of Koelling et al. (2006) and McConnell et al. (2016), who concluded that maple syrup producers have experimented with innovative tools and techniques to improve the quality and quantity of their products, resulting in an improvement in technology and subsequent increase in production. We compared our results of the state indicators relative to Wisconsin (baseline). Vermont and Maine had positive coefficients indicating higher mean yields, while other states had negative coefficients indicating lower yields compared to Wisconsin. Our positive coefficient for Vermont agrees with the study from NASS, which concluded Vermont continues to be the nation's top producer with 5.83 million liters (1.54 million gallons) of maple syrup production in 2021.

In our study predicting the maple syrup potential of Kentucky, we utilized Vermont's utilization rate of 1.44 %, 0.72 %, and 0.36 % to estimate high, medium, and low production levels, respectively, resulting in an average production potential of 816,543.61liters (215,708 gallons). This lower value for Kentucky's potential, when compared to other states, can be attributed to the utilization rate used from Vermont. However, a study conducted by Chabot (2013) revealed a much higher utilization rate for Vermont of 27 %, which if applied to our study, could have yielded a significantly higher potential for maple syrup production. The findings of this study suggested that neighboring counties in Kentucky with similar climatic conditions and average season length can exhibit significant differences in their potential maple syrup yields due to variations in the number of tappable trees and the calculated number of taps. For example, Pike County, which has approximately 8 million sugar and red maple trees ($\geq$ 33 cm DBH) according to FIA data, has a potential 116,000 taps according to NASS data, whereas the neighboring Martin County has only around 277,000 maple trees ($\geq$ 33 cm DBH) and 4009 potential taps. Furthermore, the counties located in the eastern part of the state, which is part of the Appalachian region, have higher elevations and greater densities of maple trees, as reported by the Kentucky Maple Syrup Producers Association. These areas are more conducive to sap flow and, therefore, more likely to produce a more successful maple syrup yield.

4. Conclusion

In this study, we analyzed the effects of climatic and tree variables on maple syrup yield and developed a predictive model to calculate the maple syrup potential in Kentucky. The results showed that the number of maple trees, number of taps, temperature, average season length, time, and state indicator variables significantly affect maple syrup yield. The relationship established between climatic and non-climatic factors and maple syrup yield can be applied to predict the maple syrup yield potential of a particular maple syrup-producing region at the county level in the United States. Maple syrup yield potential for Kentucky based on the 2018 reference year data showed that the state could support a maple syrup industry with an average production potential of 816,543.61 liters per tapping season. The maple syrup yield predictive model could be a useful tool for Extension agents in recruiting new maple syrup producers by assessing potential of maple syrup in a region.

Despite the contributions of this study, it has some limitations. One of the study's limitations is the use of producer-reported NASS data, which may not be entirely accurate due to missing or inconsistent values for different explanatory variables. We had to manipulate and use assumptions and calculations to fill in the missing data values. Despite the limitations, NASS is the only source that has long-term data on maple syrup from different states. Additionally, the grouping of sugar and red maple trees as 'maple trees' may be a concern since they have different sap yield potentials due to sugar content in the sap for these two species. In addition, there is no single data source that provides comprehensive information on all the variables we needed for this study, and we acknowledge that there might be some data discrepancies while using data from different sources. However, we ensured validity and authenticity of our data. Another limitation is that the potential number of taps in Kentucky was estimated using a low Vermont utilization rate based on only 2018 NASS report rather than long-term average. This may have resulted in some skewness in estimates of Kentucky's production potential. Despite these limitations, results of our study has relevance in supporting extension efforts aimed at boosting maple syrup production in Kentucky and the surrounding areas. Eq. (3)

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CRediT authorship contribution statement

Bobby Thapa: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. **Thomas O. Ochuodho:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **John M. Lhotka:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **William Thomas:** Writing – review & editing, Resources, Conceptualization. **Zachary J. Hackworth:** Writing – review & editing, Visualization, Validation, Supervision. **Jacob Muller:** Writing – review & editing, Supervision, Conceptualization. **Thomas J. Brandeis:** Writing – review & editing, Resources, Data curation. **Edward Olale:** Writing – review & editing, Supervision, Software. **Mo Zhou:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Jingjing Liang:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.tfp.2024.100649.

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