Full Paper

KULTIVAS: feasability study of a variety-location model for apple cultivation

Machbarkeitsstudie im Apfelanbau: ein Sorten-Lagen-Modell (KULTIVAS)

KULTIVAS: studio di fattibilità di un modello sito-varietale per la melicoltura

Samanta Michelini[1], Simon Tscholl[2], Johannes Erschbamer[3], Daniel Plaikner[3], Lukas Egarter Vigl[2], Walter Guerra[1]

[1]Laimburg Research Centre, 39040 Auer/Ora, BZ, Italy

[2]EURAC Research, 39100 Bolzano, Italy

[3]KONVERTO AG, 39100 Bolzano, Italy

ABSTRACT

Choosing the most-suitable locations for a given apple variety is a difficult and wide-ranging decision for farmers and all other involved parties in apple production. The selected apple variety has substantial influence on the profitability of an orchard. With KULTIVAS, we therefore propose an approach for a data-driven decision support system to deal with an ongoing problem in apple cultivation. In this project, we use selected historical apple production and quality data, modern data management systems, algorithms, machine learning techniques, and a multidisciplinary approach involving experts from different disciplines, such as agronomy, physiology, climatology, and computer science, to assess the site-specific suitability for the cultivation of specific apple varieties. Our developed prediction model is based on spatially interpolated climate and topography data, as well as apple production and quality data from different co-operatives. It can estimate various crop parameters, such as apple size, color, and yield, using available spatial information on climate. The quality of the prediction of our statistical model depends on the coverage of the possible climatic and topographic variability in the areas by the training data sets. Predictions that fall outside this confidence range have limited predictive power. It is planned to improve the results of this study with data from additional locations and more advanced algorithms for better geographical matching of sorting data, as this data set heavily influences the results.

KEYWORDS

Apple cultivar, climate, apple quality, sorting result, size, color, yield, packout, machine learning, big data, prediction model, kultivas

CITE ARTICLE AS

Michelini Samanta, Tscholl Simon, Erschbamer Johannes et.al. (2022). KULTIVAS: feasability study of a variety-location model for apple cultivation. Laimburg Journal 04/2022 DOI: 10.23796/LJ/2022.008.

CORRESPONDING AUTHOR

Samanta Michelini
samanta.michelini@yahoo.com
+390471969678

Dieses Werk ist lizenziert unter einer Creative Commons Namensnennung-Nicht kommerziell 4.0 International Lizenz.
Quest'opera è distribuita con Licenza Creative Commons Attribuzione -Non commerciale 4.0 Internazionale.
This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Für alle Abbildungen und Tabellen ohne Nennung des Urhebers gilt: © Versuchszentrum Laimburg.
Per tutte le immagini e tabelle senza menzione dell'artefice vale: © Centro di sperimentazione Laimburg.
For all figures and tables without mention of the originator applies: © Laimburg Research Centre.

BACKGROUND

South Tyrol is the main apple-growing area in Italy [1]. South Tyrol is the largest interconnected apple production area in Europe [2], covering 16 804 hectares (ha) of productive land in 2021 [3]; it is intensively cultivated with a planting density of 3000-5000 trees per hectare [4]. More than 900 000 tons of integrated and organic apples are produced here every year [5], which supplies almost up to half of the national Italian apple market, and 15% of the European market [4]. Apple production represents the main agricultural activity in the province and a source of income for thousands of families. In fact, the distinctive feature of South Tyrolean production is the presence of numerous family farms that operate on just a few hectares and that over the years have become efficiently organized and structured. The small local growers created a solid network and found new strength through cooperatives and consortia. All the various stakeholders involved either in apple production or marketing have organized themselves in a Learning and Innovation Network for Sustainable Agriculture (LINSA) [4]. In this context, the production process has been separated from processing, sales, and marketing; while the former is the responsibility of the grower, the latter is managed by the consortia, which also recommend the most suitable varieties according to market trends.

After harvest, like many fruits and vegetables, apples need to be stored under controlled atmosphere (CA) conditions to preserve firmness, flavor, and quality in general. Moreover, the maximum storage time varies between apple varieties, and different conditions are optimal for each cultivar [6]. The cooperatives in South Tyrol use state-of-the-art fruit warehouses to store apples from all their cooperative members. As soon as the cooperative decides to market a specific variety, apples are sorted and graded by sorting machines and packed in production lines.

Despite the strong identity and feeling that binds the local population to its history and tradition, in South Tyrol there is a great deal of attention to technological developments and innovations. Digital technologies are increasingly finding their way into fruit growing practice; a more efficient use of resources and reduction of environmental impact, while achieving high yields and top quality, are the main topics, as are harvesting and storage.

As in other parts of the world, crop renewal is underway in South Tyrol with multiple aims, such as the sustainable development of agriculture, but also the need to increase product diversification to meet current consumption trends and reach new markets [7]. Thus, traditional and established local varieties, such as *Golden Delicious*, *Red Delicious*, and *Fuji*, are being joined by new varieties. Many of them are distributed by clubs, consortia, or companies through vertical schemes with the aim of controlling steps of the production process, from propagation to production and marketing of the product. Club varieties are subject to patent protection and can be marked as stipulated by a licensing contract that includes either fruit quantity or quality [8]. In South Tyrol, there is an average annual renewal rate of 4.5% of the existing apple area, which involves 700 ha and more than 2.5 million trees, with a 70% preference for planting club varieties in recent years. The introduction of a new variety exposes the growers to a risk and therefore requires careful economic, agronomic, and qualitative assessments as it represents a commitment for the next 15-25 years. Factors affecting orchard viability are all to be considered by the growers, i.e., cultivar, training system, tree density, fruit quality and price [9]. In addition, the variety conversion leads to a loss of income for the grower for several years, planting costs, and possible economic losses if the variety does not reach the expected yields or certain organoleptic standards required by the club or the markets. South Tyrol is a high mountain area in the middle of the Alps and is the northernmost province in Italy [10]. The reliefs are very pronounced and comprise many mountain ranges with more than 60% of the area situated above 1600 m a.s.l. [10]. The climate is continental and affected by the insular climatic effects with relatively low annual precipitation (450-500 mm in the inner Alpine dry valley of Vinschgau), low mean annual temperature, and both high solar radiation and a high number of sunny days [10]. Moreover, its position south of the main ridge of the Alps largely protects it from Atlantic depressions, which has an impact on the weather, especially in winter [10]. Furthermore, the opening of the deep Etsch Valley to the south allows warm Mediterranean air to penetrate and mitigate the climate, especially in the southern part of the province [10]. Due to the layout of the valleys, which can be oriented according to parallels and meridians and aligned along intermediate positions [11], many microclimatic conditions occur and influence the suitability of apple production. Parallel-oriented valleys, for example, Vinschgau Valley, show strong dissimilarities between sunnier and warmer slopes with southern exposure and the colder and more humid ones with northern exposure [11]. Similar side features characterized meridian-oriented valleys, such as Etsch Valley, Eisack Valley, Sarntal, and valleys with intermediate layout, for example, Puster Valley [11]. Moreover, in the hills and mountains, a cold climate can shorten the growing season and prevent late ripening varieties from reaching maturity. In addition, high-temperature ranges could lead to reduce over coloration of the fruit and failure to reach the required standard.

Hence, an accurate estimation of the suitable location for a certain variety is essential for fruit management, apple diversification, food security, and policymaking. With KULTIVAS we therefore propose an innovative solution to an ongoing problem in the field of agriculture. This pilot project sets itself the challenge of combining knowledge and innovation to offer local associations a tool for climate-assisted varietal selection. An innovative project using selected historical production and quality data, modern data management systems, algorithms, machine learning techniques, and a multidisciplinary approach involving experts from different fields (such as agronomists, physiologists, breeders, computer scientists, ...) aims to assess the suitability for the cultivation of specific apple varieties and the achievement of quality standards, such as packout, size, and color. The tool developed is a proof of concept for a variety location model to simulate suitable areas for planting and growing a different range of apple varieties. Results could be integrated into a digital platform with interactive maps of the data used and processed, and the results achieved by the model. The specific objectives of the pilot project, the database and import process, local factors and climatic parameters evaluated, quality indices, and the variety-location model developed will be discussed in the following chapters.

OBJECTIVE

The main objective of this project is to make a feasibility study for the creation of a prediction model for apple cultivation that can forecast various apple quality parameters on a spatial basis and thereby provide a valuable decision-support system regarding site and variety selection for new plantings. In general, such geostatistical models are based on spatial data sampled in different locations and aim to find patterns and relationships that can help to identify the variability between the locations. These relationships can then be used to calculate spatial forecasts for the investigated parameters. In our case, the geostatistical model aims to identify a relationship between apple quality parameters, including yield, size and color, and topoclimatic parameters sampled from different fields. The model is thus based on spatially interpolated datasets of various topoclimatic parameters which are combined with the quality parameters. The model then analyzes the topoclimatic variability between the different fields and estimates how various climatic and topographic parameters are related to the parameters like yield, fruit size, and fruit overcolor. This relationship can then be used to generate spatial predictions for those parameters. The resulting maps will be visualized in an online portal, where they can be accessed by stakeholders and should help to identify the most suitable locations for different varieties. The fact that in this first stage only selected parameters were considered implies the actual limits of the results.

Tab. 1: Description of the basic level data used for the project (units in brackets). The data have been classified into local factor (LF), climate data (C) and quality indices (QI). The data source, providers and other details are also indicated.

Data source	Source	Detail	Reference
Digital Terrain Model, DTM	Südtiroler Bürgernetz, Geo-Katalog	Raster; Resolution 2.5 x 2.5 m	https://geokatalog.buergernetz.bz.it
Radiation Model for South Tyrol	Südtiroler Bürgernetz, GeoKatalog	Daily; Raster; Resolution 100 x 100 m	https://geokatalog.buergernetz.bz.it
Temperature Model for South Tyrol	Eurac Research, Amt für Meteorologie und Lawinenwarnung	Daily; 1996–2019; Raster; Resolution 100 x 100 m	https://wetter.provinz.bz.it
Precipitation Model for South Tyrol	Eurac Research, Amt für Meteorologie und Lawinenwarnung	Daily; 1980–2018; Raster; Resolution 100 x 100 m	https://wetter.provinz.bz.it
Fruit Register	Amt für landwirtschaftliche Informationssysteme (LAFIS)	∼ 65 000 sections; Table	https://www.provinz.bz.it
Phenological Screening	Südtiroler Beratungsring	2005–2020; Different varieties in different location; Table	https://www.beratungsring.org
Sorting Data	VIP - Verband der Vinschgauer Produzenten für Obst und Gemüse	2011–2019; 7 cooperatives; *Fuji*, *Gala*, *Golden Delicious*, *Nicoter*, *Scilate*; Table	https://www.vip.coop
Sorting Data	VOG - Verband der Südtiroler Obstgenossenschaften	2011–2019; Cooperative Fruchthof Überetsch; *Fuji*, *Gala*, *Nicoter*; Table	https://www.vog.it

DATABASE AND IMPORTANT PROCESS

For this study, we used data from various data sources and databases. Table 1 gives an overview of all the data sets that were used for this study, the data source, and references to additional information about the data owner.

The following chapters explain in more detail, which data was used, how the data was anonymized and geographically linked and, finally, cleaned and prepared to use as input for our variety-location model.

DATA OVERVIEW

The sorting data used for this project, have been provided by the two consortia involved in the project, Vinschgau Valley Cooperatives Association (VIP) and Consortium of South Tyrolean Fruit Grower's Cooperatives (VOG). VIP comprises more than 1700 fruit farms and seven cooperatives located at altitudes between 400 and 1100 m. VIP provided sorting results for *Golden Delicious*, *Fuji*, *Gala*, *Nicoter*/Kanzi®, and *Scilate*/Envy® from all its seven cooperatives from 2011 to 2019. VOG includes 12 cooperatives and 4600 fruit growers placed in the center of South Tyrol. VOG provided us the sorting data of one of its associated cooperatives in the surroundings of Bolzano for the varieties *Fuji*, *Gala*, and *Nicoter*/Kanzi® from 2011 to 2019. We analyzed the same time period and imported millions of single data points into our cloud system.

In addition to that, topographic data, including a digital elevation model (DEM) (m), exposure (°) and slope (°), was exported from the South Tyrolean GeoKatalog web portal at a 100 m resolution. Sun hours (h) and potential solar radiation (W/m2) were derived by the project team from the DEM. We also used daily data for mean, minimum, and maximum temperatures (℃) and precipitation (mm) on a 100x100 m grid that covers the whole area of South Tyrol. The dataset was interpolated based on measurements from weather stations in South Tyrol that were provided by the Weather and avalanche service of the province [12].

All commercial orchards in South Tyrol are collected in a geospatial database by the Agricultural Information Systems Office (LAFIS). This database includes detailed information for each orchard such as location, cultivated variety, planting year, production type (organic/integrated), number of trees, and area (ha).

The South Tyrolean Extension service "Südtiroler Beratungsring für Obst- und Weinbau" gathers a wide range of data in fruit growing in South Tyrol including, among other things, the annual full bloom of apple orchards. We used a dataset of different varieties and locations to predict the day of year of full bloom from 2011 to 2019. This information, in combination with the harvest time, helped us to calculate climatic and bioclimatic indicators in the annual vegetation period, respectively.

SORTING DATA ANONYMIZATION

Working with sorting results from many different farmers required that we take privacy and data ownership very seriously. For our project goals, it was not necessary to identify or save the ownership of fields. Rather, we only needed to link quality data to location (a field, located by its coordinates) and time (harvest period). This means that we removed all data points (names, personal codes, etc.) that can be considered personal information and are not directly linked to our project goals during our import process.

We have even gone one step further and used cryptographic methods for data protection and exchanged some of the apple production identification codes with hash values. A hash value is a string value of a fixed length that was calculated by a so-called hash function and uniquely identifies a given, variable-length input value. The hash value is fast to calculate, but very hard to reverse, i.e., to identify the original input value. Hash values are also highly unique, which means collisions (two different input strings generating the same hash value) are very unlikely [13]. For example, the probability of two hashes accidentally colliding for the widely used hashing function SHA-256 is approximately $4.3 \cdot 10^{60}$.

Before analyzing the provided sorting data any further, we combined all fields, field sections, and other apple production identification numbers with a static salt and generated hash values with the SHA-224 hashing algorithm. Going forward, we used this anonymized data set, and the original sorting data was not imported into our systems.

CLINING AND GEOREFERENCING OF SORTING DATA

As previously mentioned, our main challenge with the sorting data was to link each sorting result to a precise geographic location identified based on the LAFIS. In our case, on delivery after harvest, the cooperatives save the farmer's field number to identify where the apples were coming from. However, fields can be divided into many different field sections, that may contain different apple varieties or even multiple plantations with different mutants/clones or planting years for the same variety. Therefore, it was not possible to find a unique geographic location for each sorting result, and we removed all data points that could not be linked to a precise field in the LAFIS. We also filtered out data points with missing or implausible values, for instance fields with unknown orchard planting years or mismatching apple variety between delivery and plantation. Moreover, since yield and apple quality are quite different for very young trees and cannot be compared to mature orchards, we removed all sorting results that were linked to fields that were 3 years old or younger at

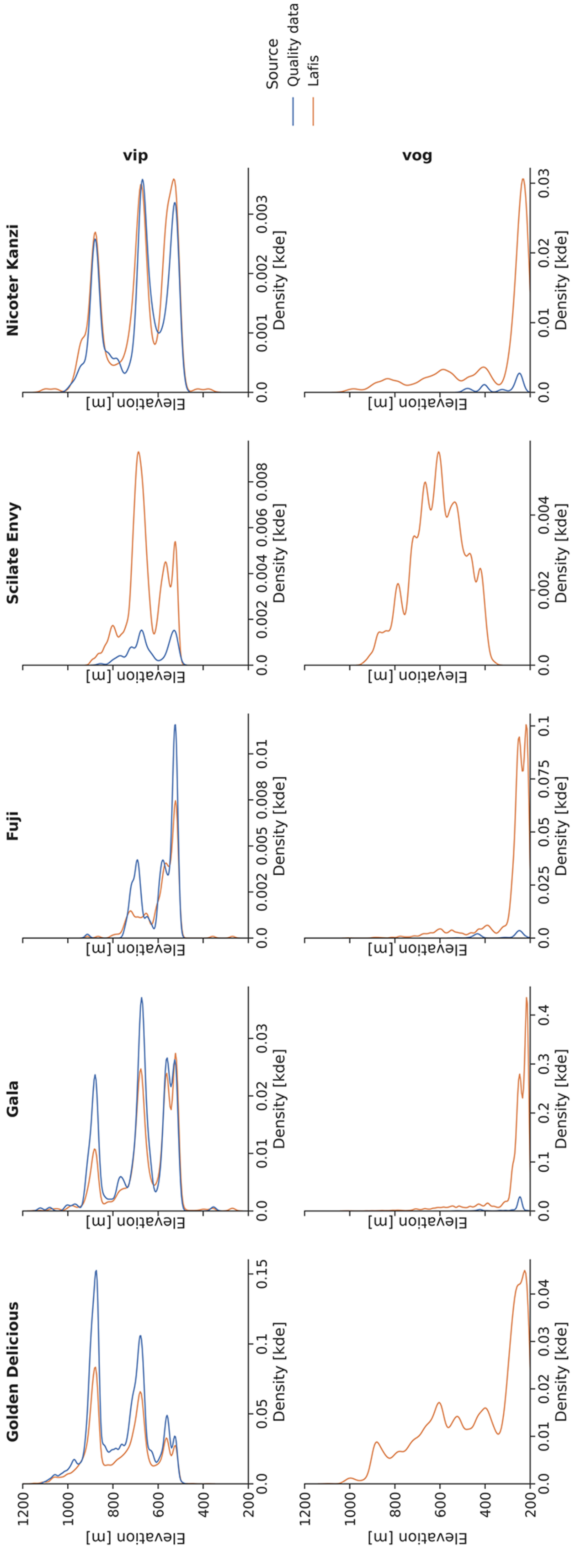

Fig. 1: Distribution of selected varieties in the South Tyrolean apple growing area.

harvest timing. For the same reasons, we also excluded apple quality data from organic orchards. The outliers were not considered either. For each apple variety, we therefore had to define a realistic yield range (t/ha) and tree count (trees/ha) and removed data points that did not match our defined criteria (Tab. 2).

Tab. 2: Description of plausible yield (t/ha) and yield (kg/plant) values used for data cleaning.

Apple variety	Yield (t/ha)		Yield (kg/plant)	
	min	max	min	max
Fuji	20	90	5	40
Gala	20	90	5	40
Golden Delicious	20	110	5	60
Nicoter/ Kanzi®	20	90	5	40
Scilate/ Envy®	20	115	5	40

FINAL SORTING DATA SET

After geolocating, filtering, and cleaning our anonymized sorting results data set, we ended up with 623 950 unique apple quality data points in the harvest seasons from 2011 to 2019 from 2164 different apple orchards in South Tyrol.

The following diagram (Fig. 1) compares the distribution of the fields that we could correctly georeferenced and link to the quality data to the overall distribution of the fields from the LAFIS dataset across different altitudes.

LOCAL FACTORS AND CLIMATIC PARAMETERS

As a matter of fact, the weather has a major influence on apple growth and development, from bud swelling to ripening, and impacts fruit characteristics and total fruit production [14] but cannot be easily regulated [15]. Identifying the main local and thermic parameters that ensure the achievement of high-quality fruit for specific cultivars can support apple growers in identifying the best variety to grow in each location and/or identify new areas for production.

LOCAL FACTORS

Due to the topographical peculiarities of the South Tyrol region, different macro- and micro-climatic conditions occur, and each location shows a different suitability for apple production. South Tyrol is a typical mountainous province with various elevation ranges and deeply cut valleys that interrupt groups and chains. The orientation of the valleys, according to parallels, meridians, or intermediate positions, reflects the disposition of mountains massifs and influences the climate [11]. Marked differences can be shown in the parallel oriented valley (e.g., Vinschgau Valley), with southern exposed sides sunnier and warmer than with northern exposed sides, which are colder and more humid, while sides of parallel oriented valleys (e.g., Etsch Valley) are more similar [11].

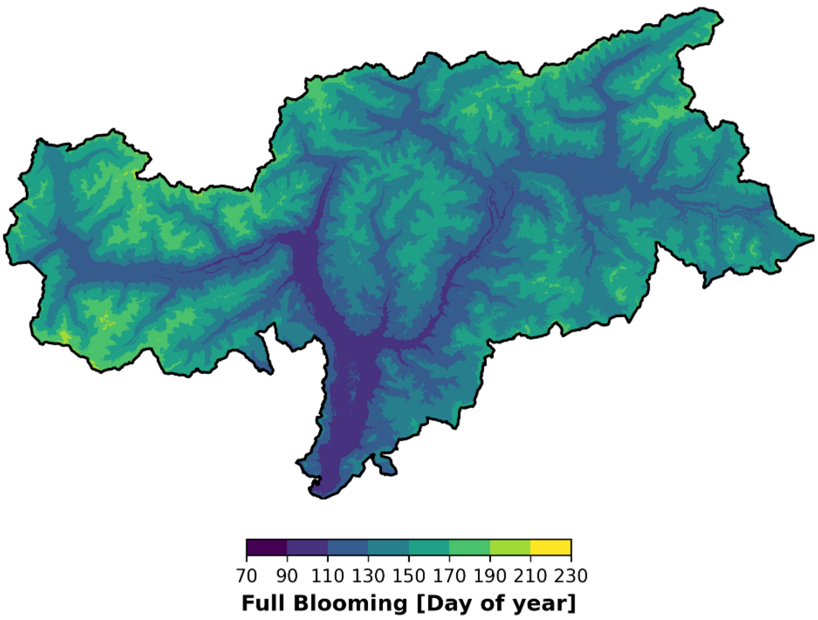

Fig. 2: Results of the full flowering forecast of *Golden Delicious* for South Tyrol. The region is colored according to the date of flowering as the day of the year; the dots represent the 57 different orchards for which flowering data were provided and are colored according to the variety planted.

Therefore, a key point of local-specific research in such a heterogeneous region is to consider all the variables explaining these differences and to be able to thoroughly describe the characteristic of each site.

In this study, elevation, exposition, potential solar radiation, and annual hours of the sun have been considered local factors (LFs). Considerations concerning orchards, the area of a section, the number of trees in each section, and the planting year were also included in the LFs type. Source and details about LFs are better explained in the above Table 1.

CLIMATIC PARAMETERS

Literature research has pointed out the climatic features that mostly influence apple growth and fruit development, hence external characteristics and yield. Climate data (C), i.e., daily mean, minimum and maximum temperatures were generated from an existing climatic model [12] and used for further calculating other needed parameters for the whole area of South Tyrol.

To deal with the determination of the bloom period, the historical full flowering dates provided by the Südtiroler Beratungsring were used. The advisory center carries out annual monitoring of the phenological stages of different apple varieties, e.g., *Braeburn*, *Fuji*, *Gala*, *Golden Delicious*, in orchards all over the province. Full blooming dates provided for the reference *Golden Delicious* were internally modeled to get the full flowering dates all over the province in annual raster files with 100 x 100 m of resolution (see an example in Fig. 2).

The annual average of the harvest dates from the sorting results was here considered the starting date of the harvest throughout the province. Cumulative annual precipitations were also calculated, but not considered due to the extensive use of irrigation practice masking the effective contribution of rainfall to fruit size and other attributes.

Besides other climatic parameters, there is an important bioclimatic indicator, the growing degree days (GDD), that was considered. It is the most common bioclimatic index used in agronomy with several applications, e.g., crop and insect development monitoring, phenological predictions, territorial and cultural/-varietal zoning. GDD represents the sum of positive daily mean temperature minus the critical one (also known as temperature base, below which growth does not progress) along a specific period and/or phenological stage. In general, GDD is evaluated for the growing season, between 1st April and 31st October, with a temperature base of 10 ℃. The selection of the proper temperature base is tricky because in most cases it strongly depends on the specific variety, phenological stage and/or adaptation to the local environment.

All measured climate attributes and the reference period are summarized in Table 3 and described in the following paragraphs.

GROWING SEASON

GDD can assess the plant's heat use efficiency. As aforementioned, the climatic features during the growing season were depicted by calculating GDDs and testing different base temperatures, i.e., 0, 4, 5, 6, 8, 10, and 12 ℃. GDDs were calculated between the canonic 1st April and 31st October and between site and, specific for the full flowering - harvest period.

Tab. 3: Description of the climatic parameters and the bioclimatic indices measured. The main period and the exact periods in which the parameters/indices were measured are also indicated. Numbers next to GDD represent the temperature base used for the calculation.

Main period	Period	Parameters	Indeces
Winter season	21st December - 20th March	sum, average and absolute minimum and maximum value of mean, minimum, maximum temperature below and over 0 ℃, and daily temperature drop below and over 0 ℃	GDD0, GDD2, GDD4, GDD5, GDD7, GDD10, GDD12, GDD15
Blossoming	+/-7 days from full bloom	count (nr. of days), sum, average and absolute minimum and maximum value of mean, minimum, and maximum temperature below 0 ℃ and daily temperature drop below 0 ℃	
Blossoming	60 days after full bloom	tmean, tmax, tmin, TR	GDD4
Summer season	n.d.	sumTover35, meanTover35, countTover35	-
Pre-harvest	21 days before harvest	sum, mean, minimum and maxium daily temperature drop	-
Growing season	1st April - 31st October	-	GDD0, GDD4, GDD5, GDD6, GDD8, GDD10, GDD12
Growing season	bloom - harvest	-	GDD0, GDD4, GDD5, GDD6, GDD8, GDD10, GDD12

WINTER SEASON

In a recent study carried out in Chile, a strong association between winter maximum temperatures and the productive performance of *Gala* was found [16]. As reported by the authors, under severe winter conditions, fruits are bigger and production higher. Considering the local winter as the period between and 21st December and 20th March, the climatic parameters measured in this research were the average and the sum of minimum, maximum, mean temperatures and daily drop temperature, the absolute minimum and the absolute maximum temperatures, the sum of temperatures below and above 0 °C, and GDD (Tab. 3). Because of the lack of supporting information on critical temperatures for each variety and for the period under examination, but in consideration of the winter dormant state, the proximity to bud break, and the dependence of blossoming to factors such as temperature history during winter [17], we tested different values, i.e., 0, 2, 4, 5, 7, 10, 12, and 15 °C.

FULL BLOOM PERIOD

The bloom period is a major stage that can seriously affect the final yield. If blossoms are damaged, fruits can improperly develop or may not develop at all. After blooming, unfavorable climatic conditions may influence the correct fruit formation in the cell division stage.

FROST RISK

As known, spring frost close to flowering can compromise harvesting. Temperatures below -2.2 °C within ten days after blossoming can damage blossoms and lead to vast yield reductions [18]. In South Tyrol, the risk is commonly countered by sprinkling orchards to cover, freeze, and protect flowers. Nevertheless, incorrect timing or management errors may have different impacts. Considering a window of +/- 7 days from full bloom and 0 °C as threshold temperature, the sum, average and absolute minimum and maximum value of the mean, minimum, and maximum temperature, and daily temperature drop have been calculated to evaluate conditions favorable to the occurrence of frost.

60 DAYS AFTER FULL BLOOM

In this period, fruits begin to develop by cell division and later on by expansion, all activities which are sensitive to temperature variations. For example, mild temperatures in the 7-21 days after flowering were found to increase the proliferation rate [19]. High temperatures lead to bigger and heavier fruits and enhance the color [20], while too high or too low temperatures reduce the final weight/size [21]. During this period, for each temperature class, i.e., mean, minimum, and maximum, the average, sum, absolute minimum, and absolute maximum value and GDD with a temperature base of 4 °C have been measured.

SUMMER SEASON

Size and quality of apples are also influenced by summer temperatures and light conditions. Several authors have highlighted and reviewed the effect of average summer temperatures on internal quality attributes, e.g., titratable acid content, anthocyanin content in the peel, sugar-acid ratio, but also to morphological characteristics, e.g., firmness [22] [23], and physiological disorders at ripening stage, e.g., *Fuji* stain, lenticel marking [24], bitter pit [25], and watercore [26]. During the development of the epidermal tissue, unfavorable climatic conditions can cause stress leading to hysteresis of specific metabolic systems resulting in peel dysfunction or aberrations [27]. Unfortunately, no critical reference temperatures were reported for the varieties in this study, so 35 °C was selected as a putative threshold above which temperatures could induce stress to certain metabolic and physiological processes. The average and the sum of temperature over 35 °C were calculated for each temperature class; also, the number of days with temperatures above 35 °C was counted.

PRE-HARVEST

The overall high quality of South Tyrolean apples depends on its climatic peculiarities. Summers are mild and as autumn approaches, the difference in temperature between day and night becomes more marked. The wide variations in temperature in the weeks just ahead of the harvest significantly influence the development of the over-color of apples. For example, a 10% increase in over-color of winter ripening varieties was observed following a 4 °C increase in the difference between daily and night temperatures in October [28]. Based on these considerations, the temperature ranges in the 21 days before the start of harvesting were averaged and summed.

QUALITY INDEX

After harvesting, apples are delivered to the cooperatives where they are weighed and sorted to ensure that specific standards are met. There is a wide variety of apples in the world, and the fruits can differ in dimension and color. Each cultivar has specific standards, and different markets may have different specifications for the same cultivar. Size, color, weight, and defects are automatically determined by the sorting systems consisting of machine vision, conveyor band, separator, and classifier [29].

Our analyzed sorting data includes data points with detailed information about apple size, color, quality class, damages, pests, and deformations that can be detected by the sorting machines. The sorting machine analyzes each individual apple with multiple cameras and sensors. After analyzing all apples for a specific delivery from a farmer, the cooperative groups apples with similar characteristics (size, color, and overall quality) in so-called quality classes.

For this project, size (caliber, mm), over or/and background color (%), yield (t/ha) and packout (highest quality share of yield) are the quality indices considered.

Fuji and *Gala* mutants are non-uniform in color, can be striped or washed, and the red coloration more or less intense; there are many clones of these polyclonal varieties, and quality standards may differ between them. Therefore, *Fuji* data were divided into *Fuji* striped and *Fuji* washed, while *Gala* was grouped into *Gala* standard, *Gala* washed, and *Gala* dark red.

Before proceeding with the model, data were subjected to intensive cleaning and filtering, as described in the "Database and import process" section, to ensure correspondence and consistency between the quality data and the local and climatic characteristics of the orchards. Quality strings were inspected and divided to extract size and color values, while yields were normalized to tons per hectare by dividing the total weight of harvested apples with the area of the field. Size, color, and yield parameters were the variables selected to be modeled. For each variable and each variety, we have defined optimal values for predicting the site suitability (Tab. 4). A combined score was also measured to provide a general overview of the potential of a location to grow varieties with optimal standards. This score summed up the three quality scores in a ratio of 33:33:33 (size, color, and packout, respectively).

SIZE (MM)

Apple fruits show a wide range of dimensions, and various markets may ask for specific sizes. There are international and national marketing standards in the fruit and vegetable sector to regulate the sale of apples. Fruits must have a diameter of at least 60 mm to be sold as Extra or Prima category according to the European Union Regulation (EU) 2019/428 [30]. In addition, the Protected Geographical Identification specification "Südtiroler Apfel PGI" has given specific size requirements for some varieties; for example, 65 mm is the minimum caliber required for *Golden Delicious* and *Fuji*, while 60 mm is required for *Gala*. Sorting machines are set up to sort apples with similar diameters and a 5 mm pitch is usually used to respond to each market demand. In our approach, for every parcel (field), the quality indicator size is defined by the share of yield with optimum size classification per year. Our definition of "optimum size" for each variety is shown in Table 4.

$$Size = \frac{Yield_{Optimum\ Size[\frac{t}{ha}]}}{Yield_{Parcel[\frac{t}{ha}]}} \cdot 100$$

COLOR (%)

The color is another important external apple trait influencing consumer preferences. Apple fruit colors range from green to yellow and red. The peel color is primarily determined by the ground color of the skin and secondarily by the anthocyanin pigmentation if present [31]. As already seen for size, either fruits epicarp color or overcolor intensity are regulated, with specific indications for each variety. In our approach, for every field, the quality indicator color is defined by the share of yield with optimum color classification per crop year. Again, our definition of "optimum color" for each variety is shown in Table 4.

$$Color = \frac{Yield_{>Optimum\ Color[\frac{t}{ha}]}}{Yield_{Parcel[\frac{t}{ha}]}} \cdot 100$$

PACKOUT

Apple is a permanent crop, and yield, together with apple quality, orchard size, number of cultivars, production costs, and specialization in organic production and/or farm gate sales were recognized as the six factors that most influence the profitability of apple production [32]. Moreover, the choice of appropriate apple varieties should be based on a long-term plan that considers the implications of the initial investment decision on the whole economic life cycle of the orchard [33]. Apple trees generally start bearing fruits in a consistent way 3 years after planting (III leaf), then production increases reaching the full fruiting period starting from year 5 (V leaf) up to around 10-20 years [34]. In our approach, for every field, the packout indicator is defined by the share of yield with highest quality classification (I quality or "prima") per crop year.

$$Packout = \frac{Yield_{Prima[\frac{t}{ha}]}}{Yield_{Parcel[\frac{t}{ha}]}} \cdot 100$$

Tab. 4: Optimal quality indices considered for the model for each variety.

Apple variety	Over Color (%)	Caliber (mm)
Fuji stripe	>50	>80
Fuji washed	>50	>80
Gala standard	>50	>70
Gala washed	>50	>70
Gala dark red	>50	>70
Golden Delicious	red-cheeked	>70
Nicoter/Kanzi®	>33	>70
Scilate/Envy®	>50	>75

VARIETY-LOCATION MODEL

After importing the data and calculating the quality indices, the following four steps were carried out to spatially predict the quality parameters:

- Geospatial join between climate and quality indices
- Model training and cross-validation
- Model selection
- Spatial predictions

To create a precise model, the topoclimatic data had to be spatially linked to the quality data (the overall approach can be seen in Fig. 3).

In the first step, the information on the climatic conditions within each parcel was combined on a geospatial basis with the quality parameters of the corresponding parcel. To associate the gridded climatic indices with the LAFIS polygons, for each index, the average value of all grid cells that fall within a LAFIS polygon was calculated. The result was then combined with the harvest quality data for each parcel to link the quality parameters with the climatic data from the same location.

The resulting information on the harvest quality under different climatic conditions was then used in the second step to train different models. The selected models ranged from very simple approaches, such as linear regression, to complex machine-learning algorithms. Each model was first used to identify the relevant climatic variables that influence harvest quality, then to quantify the influence of these relevant climatic variables on the harvest quality, and finally, to predict the harvest quality. To estimate model performance and compare the prediction error between the models, a 5-fold cross-validation approach was used. Using this approach, a subset of locations with known harvest quality was removed during model training and afterwards used to compare the predicted harvest quality with the measured harvest quality. From the results of the cross-validation, for each model the prediction error could be calculated and the models compared against each other. In order to compare the prediction accuracy of the models, various error statistics, including the mean absolute error (MAE), the root mean squared error (RMSE), and the r-squared (R^2), were calculated. Table 5 compares the different examined models. The best model was identified in the end by selecting the model that minimized the mean absolute error (MAE). Here the random forest and the cubist regression methods managed to minimize these error statistics compared to the other models and provided the best predictions.

The Cubist regression was used in the end to calculate the spatial predictions of sorting quality. Figure 4 compares the predictions from this model for each quality parameter and variety to the observed quality parameters. The closer the points are to the black, dashed line, the higher the prediction accuracy.

For all varieties except for *Scilate*, the majority of data points follow this optimum line and thus confirm a correlation between our topoclimatic variables and apple quality. R^2 values were around 0.5 for most parameters, indicating that a large portion of the variability between the locations can be explained by the model. However, there are some exceptions with smaller R^2 values caused by outliers with high differences between model predictions and observed quality (for instance, the optimum size for *Golden Delicious*). Also, the mean absolute error (MAE) depends on variety and parameter. On average, the highest error was observed for *Fuji*, followed by *Gala* standard and *Nicoter*. The smallest error was observed for *Golden Delicious*, most likely because of the increased data availability for this variety. Additionally, the optimum size and optimum color indices were associated with a higher error than the packout for all varieties except for *Golden Delicious*. Only for *Scilate*, no significant relationship between our topoclimatic variables and the quality indices could be identified, which results in predictions that are not correlated to the observed quality parameters. Most likely, this is caused by the low amount of available data for this variety.

In the last step, the previously identified model was used to spatially predict the quality indices across South Tyrol for each of our selected varieties. For each quality index, a separate prediction was calculated on a continuous 100x100 m grid. The predicted values were then standardized onto a scale that ranges from 0 to 1 to make the different indices comparable. Additionally, we restricted the area of predictions for some of our varieties, as their quality data for certain elevation ranges were lacking as seen in Figure 1.

Finally, the continuous predictions were spatially linked to the LAFIS polygons by calculating the mean of all grid cells within a polygon. The result contains the spatial information for each apple field and the corresponding predictions for each specific variety and quality parameter (size, color, and packout). This file was then further used to visualize the cultivation suitability of our selected apple varieties on an interactive map in our web portal.

DISCUSSION

This variety-location study for apple cultivation demonstrates the viability of a machine learning approach using big data to predict agricultural suitability. The Cubist model used recognizes the statistical relationship between the predictor variables (climate and topography) and the quality indicators (color, size, packout) and decides the influence of these variables in the model definition, depending on the variety. Our statistical model can predict the quality indicators more accurately the better the training data set covers the possible climatic and topographic variability in the areas. Pre-

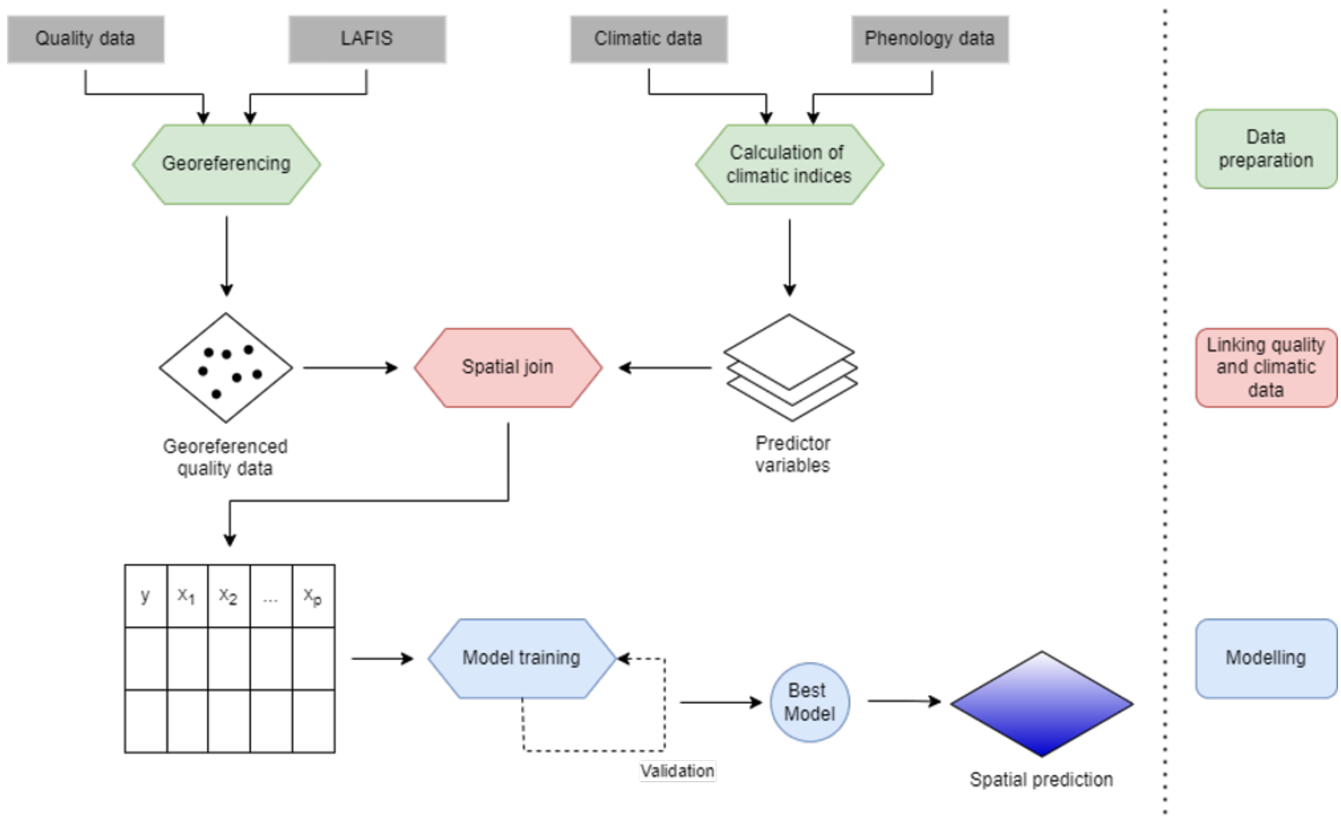

Fig. 3: Overview of the Variety-location modelling experiment workflow.

dictions that fall outside this confidence range have limited predictive power.

The diagram (Fig. 1) seen in the "Databases and Import" section displays the distribution in South Tyrol of the varieties selected for this experiment. One current limitation in our approach that can be observed in this figure is the limited data availability of apple quality data in some areas. The quality data that was provided to us includes sorting data from several locations. However, from the elevation density distribution of the fields, one can see that a lot of potential for more data points exists, either with sorting data from additional cooperatives or with improved algorithms that match more sorting results to geographic locations. As mentioned in the "Database and Import" chapter, a lot of data couldn't be considered for our model, as we couldn't create reliable geospatial linkage to the different apple fields. One of the reasons for this is that the historical plantation data that LAFIS provides is rather new and doesn't reach that far back in time.

Another encountered source of limitation is the sorting data itself. The quality data of the cooperatives have some unknowns that we could not validate and therefore we can't be sure how accurate they are. The calibration of sorting machines can change over the years. The definition of color and quality classes changes as time goes on. We also have the differences in sorting machines between VIP and VOG. As they are not identical, they are likely to have some variance in them.

Speaking about data quality, let's mention some problems with the quantity of the said data. Our data distribution per variety in the original data is a challenge in itself. Most data points are for *Golden Delicious*, and little data is given for other varieties. Consequently, the created models cannot work equally well for all varieties. For instance, the model for the variety *Scilate* showed us that with little to no available data points, no significant relationship between our topoclimatic variables and the quality indices could be identified.

For some varieties, we do not have quality data from all the elevation levels where this variety is cultivated, especially in the VOG dataset where we still have lots of potential with additional data points from fields and cooperatives that were not considered in this project. For the VIP dataset, most varieties are well represented in our quality data, except for *Sciate*, for which we have only very little data. Considering the elevation ranges covered by the quality data is important, as the model can only produce reliable predictions for those elevation levels where we also have a sufficient amount of quality data. For instance, the predictions for the variety *Fuji* were limited to an elevation range up to 800 m a.s.l., as we do not have enough quality data from fields at elevations above 800 m a.s.l. to produce reliable predictions in these areas. Similarly, for the VOG data, the predictions for all varieties were restricted to the area covered by its cooperative in the vicinity of Bolzano, because the areas outside are strongly underrepresented in our quality data.

Also, it needs to be underlined that the selection and weighting of quality criteria (optimal size, color) strongly influence the results. Our approach used predicts results based on suitability. These resulting indicators have to be understood as relative to other fields and not as "absolute" suitability. Meaning that suitability is only given compared to other locations of interest. In addition to that, the spatial resolution of predictions is limited to 1 ha (100x100 m) as the climatic data is currently limited to that accuracy.

At this stage, with the variety-location study described here, it is not possible to explain all the variability between the fields because some factors are not considered in our model. For example, the soil or the influence of the management by the farmers are not part of the model: their inclusion could improve the performance of the model (R^2 and MAE).

To summarize, the reliability of our predictions is impacted by the availability of diverse variety-location information. Our results suggest that with the current approach it is unfeasible to attempt to make predictions outside of the confidence range provided by our initial data. With that in mind, for now, a spatial forecast is calculated only for those areas and varieties that are also supported by a sufficient data framework or statistical context. One of the future improvements and goals could be the creation of a prediction model over the whole region of South Tyrol. But to make this possible, several of the previously mentioned limitations must be overcome, the most important one being the improvement of the data model with more diversified information from different locations. Additionally, extending the range of supported varieties is highly desirable and might be further worked on.

Tab. 5: Comparison of different modeling strategies. Model types an mean error statistics across all three quality indicators. MAE = Mean Absolute Error, RMSE = Root Mean Squared Error.

Model type	MAE	RMSE	R^2
Random Forest (1)	3,38	5,1	0,86
Cubist Regression (2)	3,41	5,17	0,84
CART (3)	3,75	5,74	0,83
Regularized Gradient Boosting (4)	4,17	6,66	0,77
Support Vector Machine (5)	4,24	7,73	0,71
Nearest Neighbour (6)	4,26	6,93	0,75
Neural Network (7)	4,91	7,73	0,69
MARS (8)	4,99	7,85	0,7
Lasso Regression (9)	5,67	8,83	0,55
Linear Regression (10)	5,687	8,83	0,55
Ridge Regression (9)	5,91	8,92	0,55

(1) Wright MN, Wager S, Probst P. ranger: A Fast Implementation of Random Forests. 2021; Available from: https://github.com/imbs-hl/ranger
(2) Kuhn M, Quinlan R. Cubist: Rule- And Instance-Based Regression Modeling. 2022; Available from: https://CRAN.R-project.org/package=Cubist
(3) Therneau T, Atkinson B. rpart: Recursive Partitioning and Regression Trees. 2019; Available from: https://CRAN.R-project.org/package=rpart
(4) Chen T, He T, Benesty M, Khotilovich V, Tang Y, Cho H, et al. xgboost: Extreme Gradient Boosting. 2022; Available from: https://github.com/dmlc/xgboost
(5) Karatzoglou A, Smola A, Hornik K. kernlab: Kernel-Based Machine Learning Lab. 2019; Available from: https://CRAN.R-project.org/package=kernlab
(6) Schliep K, Hechenbichler K. kknn: Weighted k-Nearest Neighbors. 2016; Available from: https://github.com/KlausVigo/kknn
(7) Ripley B. nnet: Feed-Forward Neural Networks and Multinomial Log-Linear Models. 2021; Available from: http://www.stats.ox.ac.uk/pub/MASS4/
(8) Milborrow S. earth: Multivariate Adaptive Regression Splines. 2021; Available from: http://www.milbo.users.sonic.net/earth/
(9) Friedman J, Hastie T, Tibshirani R, Narasimhan B, Tay K, Simon N. glmnet: Lasso and Elastic-Net Regularized Generalized Linear Models. 2021; Available from: https://CRAN.R-project.org/package=glmnet
(10) Team RC. R: A Language and Environment for Statistical Computing. 2020; Available from: https://www.R-project.org/.

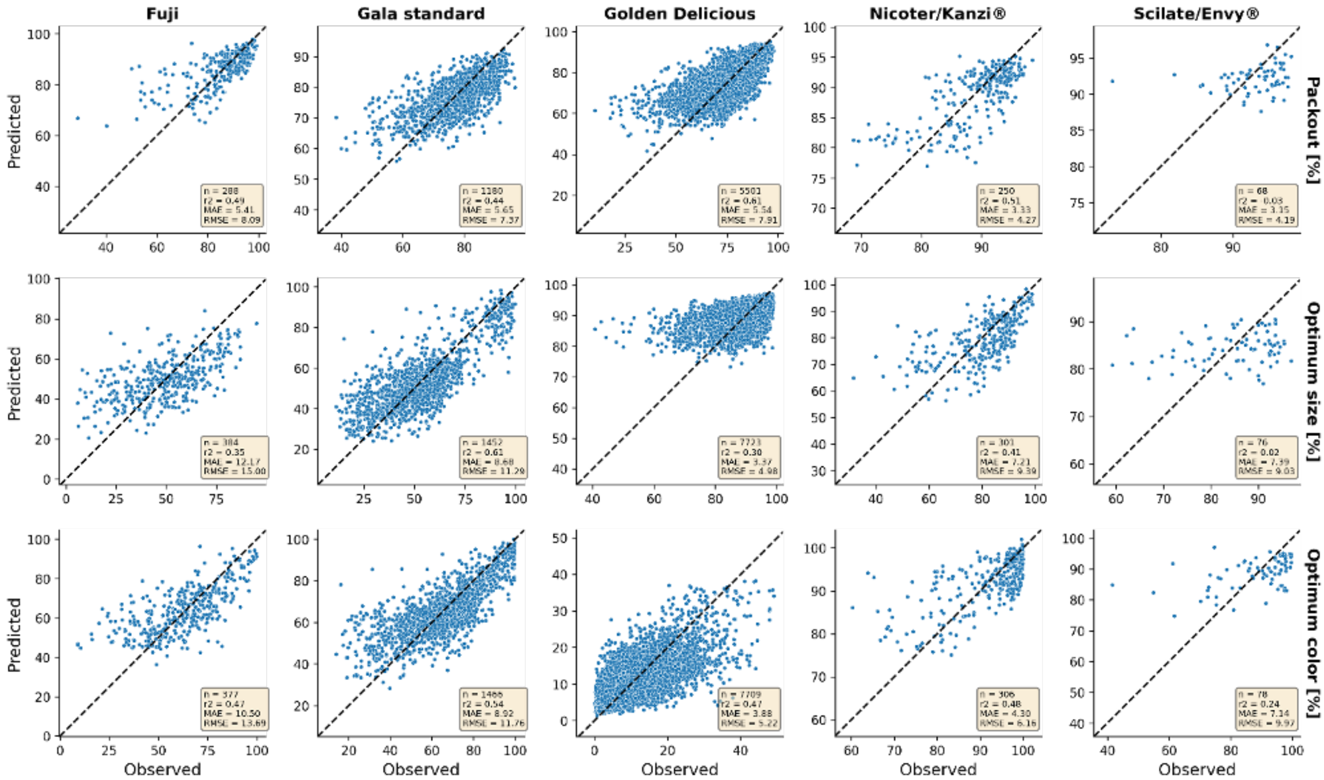

Fig. 4: Predicted quality parameters for each variety.

In conclusion, there is still lots of improvement possible and some parts can be tested and conducted in a different way. To improve the validity of this study in this area, one should first focus on improving data quantity and quality, as this heavily influences the results.

ACKNOWLEDGMENTS

We would like to express our sincere thanks to the two consortia VIP ("Verband der Vinschgauer Produzenten für Obst und Gemüse") and VOG ("Verband der Südtiroler Obstgenossenschaften"), LAFIS ("Amt für landwirtschaftliche Informationssysteme") and SBR ("Südtiroler Beratungsring für Obst- und Weinbau") for providing data, assistance, and feedback at all stages of the project. Special thanks to all KONVERTO, Laimburg Research Centre, and EURAC Research employees and collaborators who worked or gave support to the working group and to all those who directly or indirectly participated and contributed.

ZUSAMMENFASSUNG

Die Wahl des am besten geeigneten Standortes für eine bestimmte Apfelsorte ist für Landwirte, und alle anderen an der Apfelproduktion beteiligten Organisationen, eine schwierige und weitreichende Entscheidung. Die gewählte Kombination hat über viele Jahre hinweg erheblichen Einfluss auf die Wirtschaftlichkeit einer Apfelwiese. Vor diesem Hintergrund schlagen wir mit KULTIVAS einen Ansatz zur datengestützten Hilfestellung für ein aktuelles Problem im Bereich des Apfelanbaus vor. In diesem Projekt nutzen wir ausgewählte historische Qualitätsdaten aus der Apfelproduktion, moderne Datenmanagementsysteme, Algorithmen, Techniken des maschinellen Lernens und einen multidisziplinären Ansatz, an dem Experten aus verschiedenen Bereichen wie Agronomie, Physiologie, Klimatologie und Informatik beteiligt sind, um die Standorteignung für den Anbau bestimmter Apfelsorten zu bewerten und vorherzusagen. Das von uns entwickelte Prognosemodell basiert auf räumlich interpolierten Klima- und Topographiedaten sowie auf Ertrags- und Qualitätsdaten von verschiedenen Obstgenossenschaften. Es kann verschiedene Anbauparameter wie Apfelgröße, -farbe und -ertrag anhand räumlich verfügbarer Klimadaten vorhersagen. Unser statistisches Modell kann die Qualitätsindikatoren umso genauer vorhersagen, je besser der Trainingsdatensatz die mögliche klimatische und topografische Variabilität in den Gebieten abdeckt. Vorhersagen, die außerhalb dieses Vertrauensbereichs liegen, haben eine begrenzte Vorhersagekraft. Es ist geplant, die Ergebnisse dieser Studie mit Daten von zusätzlichen Standorten und verbesserten Algorithmen zur Georeferenzierung von Sortierdaten zu verbessern, da diese Datensätze die Ergebnisse stark beeinflussen.

RIASSUNTO

Scegliere le zone più idonee per la coltivazione di una determinata varietà è una decisione difficile e di ampio spettro che coinvolge non solo gli agricoltori, ma tutta la filiera coinvolta nel processo, dalla produzione alla vendita. La scelta varietale ha ripercussioni economiche di lungo termine. In tale prospettiva, con KULTIVAS vorremmo proporre un approccio data-driven a questo importante problema del settore melicolo. In questo progetto, dati storici selezionati sulla produttività e qualità delle mele, moderni sistemi di gestione dei dati, algoritmi e tecniche di apprendimento automatico sono stati impiegati adottando un approccio multidisciplinare che coinvolge esperti di diversi settori, quali agronomia, fisiologia, climatologia e informatica, per valutare l'idoneità sito- specifica alla coltivazione di determinate varietà di mele. Il modello di previsione sviluppato nell'ambito del progetto si basa su dati climatici e topografici interpolati spazialmente, oltre che su dati di produzione e qualità delle mele provenienti da diverse cooperative altoatesine. Usando informazioni spazialmente disponibili sul clima, il modello è in grado di stimare vari parametri di produzione, come calibro, colore e resa. La previsione degli indicatori predetti dal modello statistico è più precisa quanto più il set di dati di training copre la variabilità climatica e topografica delle aree di indagine. In aree con caratteristiche al di fuori di questa variabilità, il modello avrà un potere predittivo limitato. I risultati di questo studio saranno arricchiti con dati provenienti da altre località e valutando ulteriori algoritmi per la corrispondenza geografica dei dati di cernita, in quanto il set di dati influenza in maniera importante i risultati.

REFERENCES

[1] Mantinger H. (1998). The south tyrolean apple plantating system. Acta Horticulturae 513, 279-286, DOI: 10.17660/ActaHortic.1998.513.33.

[2] Carneiro G.A., Baric S. (2021). Colletotrichum fioriniae and Colletotrichum godetiae causing postharvest bitter rot of apple in South Tyrol (Northern Italy). Plant Disease 105 (10), 3118-3126, DOI: 10.1094/PDIS-11-20-2482-RE.

[3] ISMEA Mercati (ed.) (2021). Frutta invernale. Focus mele. Tendenze Frutta fresca (3). Retrieved December 21, 2021, from https://www.ismeamercati.it/flex/cm/pages/ServeAttachment.php/L/IT/D/1%252Fa%252F8%252FD.a809b7bed488e3e09737/P/BLOB%3AID%3D11875/E/pdf.

[4] de Meyer J. (2014). Apple-producing family farms in South Tyrol. An agriculture innovation case study. (Occasional Papers on Innovation in family farming). Food and Agriculture Organization of the United Nations, Rome, Italy, DOI: 10.13140/RG.2.2.22157.18406.

[5] Provincia Autonoma di Bolzano - Ripartizione Agricoltura (ed.) (2020). Relazione agraria e forestale 2020. Retrieved February 10, 2022, from https://www.provincia.bz.it/agricoltura-foreste/agricoltura/relazione-agraria-forestale.asp.

[6] Bai J., Baldwin E.A., Goodner K.L. et al. (2005). Response of four apple cultivars to 1-methylcyclopropene treatment and controlled atmosphere storage. HortScience 40 (5), 1534-1538, DOI: 10.21273/HORTSCI.40.5.1534.

[7] CBI - Centre for the Promotion of Imports from Developing Countries (2021). The European market potential for apples. Retrieved February 10, 2022, from https://www.cbi.eu/market-

information/fresh-fruit-vegetables/apples/market-potential.

[8] Asioli D., Canavari M., Malaguti L. et al. (2016). Fruit branding. Exploring factors affecting adoption of the new pear cultivar 'Angelys' in Italian large retail. International Journal of Fruit Science 16 (3), 284-300, DOI: 10.1080/15538362.2015.1108894.

[9] Lordan J., Gomez M., Francescatto P. et al. (2019). Long-term effects of tree density and tree shape on apple orchard performance. A 20-year study – part 2, economic analysis. Scientia Horticulturae 244, 435-444, DOI: 10.1016/j.scienta.2018.03.031.

[10] Wilhalm T. (2018). Floristic Biodiversity in South Tyrol (Alto Adige). In: Pedrotti F. (ed.). Climate gradients and biodiversity in mountains of Italy. (Geobotany Studies). Springer, Cham, Germany, pp. 1-17, DOI: 10.1007/978-3-319-67967-9_1.

[11] Pedrotti F. (ed.) (2018). Climate Gradients and Biodiversity in Mountains of Italy. (Geobotany Studies) Springer Nature, Cham, Germany, here pp. 51-81, DOI: 10.1007/978-3-319-67967-9.

[12] Tscholl S., Tasser E., Tappeiner U. et al. (2021) Coupling solar radiation and cloud cover data for enhanced temperature predictions over topographically complex mountain terrain. International Journal of Climatolology 42 (9), 4684-4699, DOI: 10.1002/joc.7497.

[13] Gilbert H., Handschuh H. (2004). Security Analysis of SHA-256 and Sisters. In: Matsui M., Zuccherato R.J. (eds.). Selected Areas in Cryptography. SAC 2003. (Lecture Notes in Computer Science ; 3006). Springer, Berlin, Heidelberg, Germany, pp. 175–193, DOI: 10.1007/978-3-540-24654-1_13.

[14] Chaves B., Salazar M.R., Schmidt T. et al. (2017). Modeling fruit growth of apple. Acta Horticulturae 1160, 335-340, DOI: 10.17660/ACTAHORTIC.2017.1160.48.

[15] Zhang Q., Bei-bei Z., Min-ji L. et al. (2018). Multivariate analysis between meteorological factor and fruit quality of Fuji apple at different locations in China. Journal of Integrative Agriculture 17 (6), 338-347, DOI: 10.1016/S2095-3119(17)61826-4.

[16] Reginato G., Mesa K., Riquelme C. (2019). Fruit size and yield efficiency of "Gala" apples grown in Chile depend on winter temperatures and season length. European Journal of Horticultural Science 84 (3), 124-130, DOI: 10.17660/eJHS.2019/84.3.2. .

[17] Pfleiderer P., Menke I., Schleussner, C.F. (2019). Increasing risks of apple tree frost damage under climate change. Climatic Change 157, 515-525, DOI: 10.1007/s10584-019-02570-y.

[18] Unterberger C., Brunner L., Nabernegg S. et al. (2018). Spring frost risk for regional apple production under a warmer climate. PLoS ONE 13 (7), DOI: 10.1371/journal.pone.0200201.

[19] Calderón-Zavala G., Lakso A.N., Piccioni R.M. (2004). Temperature effects on fruit and shoot growth in the apple (Malus domestica) early in the season. Acta Horticulturae 636, 447-453, DOI: 10.17660/ActaHortic.2004.636.54.

[20] Warrington I., Fulton T., Halligan E. et al. (1999). Apple fruit growth and maturity are affected by early season temperatures. Journal of the American Society for Horticultural Science 124 (5), 468-477, DOI: 10.21273/JASHS.124.5.468.

[21] Forshey C.G. (1990). Factors affecting "Empire" fruit size. Proceeding of the annual meeting of the New York State Horticultural Society 135, pp. 71-74.

[22] Qu Z., Zhou G. (2016). Possible impact of climate change on the quality of apples from the major producing areas of China. Atmosphere 7 (9), 113, DOI: 10.3390/atmos7090113.

[23] Tromp J. (1990). Fruit shape in apple under various controlled environment conditions. Scientia Horticulturae 43 (1-2), 109-115, DOI: 10.1016/0304-4238(90)90042-D.

[24] Schrader L.E., Sun J., Felicetti D. et al. (2003). Stress-induced disorders. Effects on apple fruit quality. In: Conference Paper for the Washington Tree Fruit Postharvest Conference, Wentachee, Washington, USA, 2003. Washington State Horticulture Association, Wentachee, Washington, USA, pp. 1-7.

[25] Hall E.G., Scott, K.J. (1989). Pome Fruit. In: Beattie B.B., McGlasson W.B., Wade N.L. (eds.) Postharvest Diseases of Horticultural Produce. Vol. 1. Temperate Fruit. CSIRO, Australia.

[26] Ferguson I.B., Watkins C. B. (1989). Bitter pit in apple fruit. Horticultural Reviews 11, 289-355, DOI: 10.1002/9781118060841.ch8.

[27] Curry E.A., Torres C., Neubauer L. (2008). Preharvest lipophilic coatings reduce lenticel breakdown disorder in "Gala" apples. HortTechnology 18 (4), 690-696, DOI: 10.21273/HORTTECH.18.4.690.

[28] Lakatos L., Biniak-Pierog M., Zyromski A. (2012). Effect of night and day temperature on the cover colour and quality parameters of apple. Journal of Water and Land Development 16 (I-VI), 23-28, DOI: 10.2478/v10025-012-0020-1.

[29] Sofu M., Er O., Kayacan M. et al. (2016). Design of an automatic apple sorting system using machine vision. Computers and Electronics in Agriculture 127, 395-405, DOI: 10.1016/j.compag.2016.06.030.

[30] The European Commission (ed.) (2018). Commission Delegated Regulation (EU) 2019/428 of 12 July 2018 amending Implementing Regulation (EU) No. 543/2011 as regards marketing standards in the fruit and vegetables sector. Retrieved February 10, 2022, from http://data.europa.eu/eli/reg_del/2019/428/oj)

[31] Dar J.A., Wani A.A., Ahmed M. et al. (2019). Peel colour in apple (Malus x domestica Borkh.). An economic quality parameter in fruit market. Scientia Horticulturae 244, 50-60. DOI: 10.1016/J.SCIENTA.2018.09.029.

[32] Dorin B., Arion F., Muresan I. et al. (2015). Evaluation of economic efficiency of apple orchard investments. Sustainability 7 (8), 10521-10533 DOI: 10.3390/su70810521.

[33] Català L.P., Durand G.A., Blanco, A.M. et al. (2013). Mathematical model for strategic planning optimization in the pome fruit industry. Agricultural Systems 115, 63-71, DOI: 10.1016/j.agsy.2012.09.010.

[34] Ta N., Chang Q., Zhang Y. (2021). Estimation of apple tree leaf chlorophyll content based on machine learning methods. Remote Sensing 13 (19), 3902, DOI: 10.3390/rs13193902.