RESEARCH ARTICLE

Coupling solar radiation and cloud cover data for enhanced temperature predictions over topographically complex mountain terrain

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Abstract

Fine-scale climate information is critical to understand species–climate relationships. It is usually obtained by interpolating meteorological station data or by downscaling coarse-gridded climate data. In mountain areas, however, the low station density and macroclimate variables used in coarse-gridded climate products cannot reproduce fine-scale variations caused by the complex topography and thus result in biased predictions of species responses to climate change. Here, we present an innovative method to estimate daily local air temperature at 100 m spatial resolution in the mountain region of South Tyrol (Central Alps, Italy), called the cloud-corrected model. We introduce a correction factor that couples solar radiation and cloud cover data to improve air temperature predictions. Results are compared to models that either consider elevation only (lapse-rate model) or elevation and solar radiation but not cloud cover (clear-sky model) using a set of independent meteorological stations for validation. Moreover, all models were tested to predict critical phenological stages of the climate-sensitive species \textit{Vitis vinifera}. Over the vegetative period, the cloud-corrected model significantly reduced the mean absolute error of predicted temperature compared with the lapse rate and clear-sky model by 10 and 23\%, respectively, and the bias by 93 and 90\%, respectively. Solar radiation and cloud cover both strongly influenced local air temperature and their inclusion in temperature estimates greatly reduced systematic biases and improved predictions of important plant phenological stages by multiple days. Our method therefore provides a new way to include easily accessible topography and climate data into fine-scale temperature predictions and accounts for important climate forcing factors that otherwise are often neglected. It combines efficiency and accuracy, because it limits data requirements but still operates on an ecologically relevant spatial scale. Thus, our approach offers promising opportunities to improve the understanding of species–climate relationships, especially in regions sensitive to the effects of climate change.

KEYWORDS
aspect, climate niche, grapevines, lapse rate, microclimate, phenology, slope, topoclimate
1 | INTRODUCTION

Local climate conditions are critical to species development and habitat distribution. Reliable assessments of species reaction to climate change require climate data that adequately capture both ecosystem structures and processes to establish a direct link between climate, the target species and its habitat (Gardner et al., 2019). However, the coarse spatial scale at which climate is usually modelled is different from the fine spatial scale at which organisms experience it (Jucker et al., 2020; Lembrechts and Nijs, 2020; Zellweger et al., 2020). Ecological models are frequently based on macroclimate data, such as WorldClim (Fick and Hijmans, 2017) or CHELSA (Karger et al., 2017), which are easily accessible and cover large geographic areas. Such products, however, represent free-air climate patterns at spatial resolutions of 1 km or coarser and thus fail to fully capture fine-scale variations that are critical for species performance and distribution (Lenoir et al., 2017).

Most assessments of species responses to climate change are therefore limited by a lack of accurate climate data at organism-relevant scales. For instance, phenological plasticity is an important trait that determines species habitat ranges as well as their adaptive capacity to climate change (Chuine, 2010). However, the phenological development can be very sensitive to local climate conditions and strongly vary over short distances (Hwang et al., 2011; Ward et al., 2018). Macrometeorological variables do not reflect such fine-scale variations and therefore often result in misleading predictions of climate change impacts (Barton et al., 2019). Both mechanistic and correlational approaches that are often used to assess species reaction to changing climate thus require accurate information on local climate conditions to derive reliable conclusions (Bramer et al., 2018). This is particularly true of regions with heterogeneous terrain, such as mountain areas, where elevation, slope and aspect can change over short distances, creating highly dynamic local climate patterns (Scherr and Körner, 2010; Suggitt et al., 2011; Meineri et al., 2015) often referred to as topoclimate (Bramer et al., 2018). To better understand how species respond to local climate variations, it is thus crucial to use climate information at a fine-scale that also accounts for relevant climate-forcing factors.

Unfortunately, spatial data on local climate conditions are still lacking for most mountain areas because of the limited density of meteorological stations and their complex topography. Recently, Kearney et al. (2020) presented a promising method to model fine-scale climate from data with global coverage. The underlying models use biophysical equations to estimate near-surface climate variations; thus, these methods are easily applicable to different geographic regions (Kearney and Porter, 2017; Maclean et al., 2019). However, they were developed and tested for terrain with smaller elevation ranges and simpler topography than mountain areas and use coarse-gridded, globally available data with resolutions of several kilometres. Such coarse-gridded data cannot reproduce the climate variability generated by local topography, which is a crucial factor in mountain areas (Potter et al., 2013). Other, more location-specific methods typically use climate data measured by standardized meteorological stations, well-distributed around the world, to downscale or interpolate climate variables. These stations, however, are purposefully located to minimize local climate variations; therefore, their data cannot fully represent complex mountain terrain (WMO, 2018). As a consequence, models based on standardized meteorological station data underestimate fine-scale climate variability related to local topography (Aalto et al., 2017; Meineri and Hylander, 2017). To overcome this issue, extensive networks of field data loggers have been used either to measure fine-scale climate conditions directly near the habitat of the target species, or to acquire additional calibration data (Ashcroft and Gollan, 2012; Greiser et al., 2018; Macek et al., 2019). However, such field measurements are typically characterized by short temporal and geographic ranges and high maintenance costs (Lembrechts et al., 2019). Finally, remote sensing observations offer interesting new opportunities to estimate fine-scale climate conditions, especially for areas with sparse station coverage (Oyler et al., 2015; Holden et al., 2016; Stewart and Nitschke, 2017). The availability of remote sensing data is rapidly increasing but the geographic coverage and spatiotemporal resolution are still limiting factors (Zellweger et al., 2019).

Furthermore, most ecological models use potential solar radiation variables but do not account for spatiotemporal variations of cloud cover (Lenoir et al., 2017; Meineri and Hylander, 2017; Macek et al., 2019), which is especially problematic in mountain areas because they are amongst the regions with the highest variability of cloud cover (Wilson and Jetz, 2016). Cloud cover dynamics strongly influence incoming solar radiation, and thus also local climate patterns, at surface level. In clear-sky conditions, for example, surface radiation is mostly direct, and strong topoclimate patterns can form. If cloud cover increases, diffuse radiation also increases and topoclimate patterns weaken (Geiger et al., 2009). This can have important implications for ecological studies because local climate might be highly different in overcast versus clear-sky conditions.

In this study, we introduce the cloud-corrected model, a new method to model daily, fine-scale air temperature in topographically complex mountain terrain. Our aims are to (a) introduce a flexible method to model local air temperature for mountain environments that can easily
be applied in other regions, (b) demonstrate the importance of fine-scale climate for ecological studies in mountain areas, and (c) quantify the effect of topography and cloud cover on local air temperature. As a study area, we use the Autonomous Province of South Tyrol (Italy), a mountainous region in the Eastern Italian Alps, but the present method is easily transferable to other geographic areas. Furthermore, we provide example data and calculation steps in the freely accessible “topoclim” package for the R software (hereafter R-package) (Tscholl, 2021).

2 | MATERIALS AND METHODS

2.1 | Study area

The study area is the Autonomous Province of South Tyrol (Italy) in the Central Alps (Figure 1). Total surface area is about 7,400 km² and elevation ranges from 200 to 3,950 m above sea level (a.s.l.). The study area is characterized by a complex topography; in more than half of the territory, terrain slope ranges between 20° and 40°. Settlements and permanent cultures, such as apple production or arable land, dominate in lower altitudes and flat areas. Intermediate elevations and steeper slopes are covered by forests and pastures. Highest elevation areas are predominantly covered by summer pastures, alpine grasslands, rocks and glaciers.

2.2 | Data and software

Two groups of meteorological stations are considered: official and validation stations (Figure 1). All stations measure 2 m air temperature and solar irradiance on an hourly basis. Daily mean air temperature was calculated by averaging the hourly temperature measurements and daily solar insolation was obtained by summing up the hourly irradiance measurements. The official station network includes 15 stations maintained by the Hydrological Office of the Province of Bolzano. Their locations are standardized in accordance with World Meteorological Organization (WMO) guidelines (WMO, 2018). They are evenly distributed in the study area, with elevations of up to 1,600 m (Table S1, Supporting Information). For seven official stations, daily records are available over a longer period of 6–30 years. The validation stations include 26 meteorological stations with elevations of 200 to 1,100 m a.s.l., which cover topographically more complex terrain than the official network (Figure S1 and Table S2). For details about the measurement sensors of the validation stations, see Data S1.

The DEM used in this study can be downloaded from https://land.copernicus.eu/ at 25 m resolution. The original DEM was resampled to 100 m resolution by bilinear interpolation.

The following calculations were performed using the R Software, version 4.0.2 (R Core Team, 2020),
including the “raster” package, version 3.4.5 (Hijmans, 2020), and the ArcGIS software, version 10.6.1 (Esri, 2019). For transferability, calculation code and example datasets are provided in the R-package “topoclim,” freely accessible at https://github.com/sitscholl/topoclim (Tscholl, 2021).

### 2.3 Interpolation methods

Three different interpolation methods were used in this study (Figure 2). The lapse-rate model consists of a linear regression with elevation as explanatory variable and does not consider terrain aspect or slope. Predictions from the lapse-rate model therefore represent air temperature on a flat surface (Figure 2a). The clear-sky model builds on the lapse-rate model but also accounts for air temperature variations related to slope, aspect and solar position using the relative radiation factor (Figure 2b). The cloud-corrected model additionally includes the effect of cloud cover on local air temperature. In contrast to the clear-sky model, the cloud-corrected model combines the cloud index (Figure 2c) with the relative radiation factor (Figure 2b) to account for cloud cover effects on incoming solar radiation.

#### 2.3.1 Lapse-rate model

The lapse-rate model consists of a linear regression with the following form (Kuhn and Johnson, 2013),

\[
\text{Air temperature on flat surface} = \text{Measured air temperature} + \text{Lapse-Rate model}.
\]

**FIGURE 2** Flowchart showing the calculation steps for all three interpolation methods. (a) Shows the lapse-rate model, (b) the relative radiation factor and (c) the cloud index. Results from (a, b) are used to calculate the clear-sky model and results from (a–c) to calculate the cloud-corrected model. The circles refer to different calculation steps; the corresponding equation number from the main text is indicated next to the circles.
Finally, temperature predictions from the clear-sky model were calculated by combining the lapse-rate model output, the relative radiation factor $\Delta_{\text{rad}}$ and the empirical conversion factor $m_{\text{rad}}$ between solar insolation and air temperature. The empirical correction factor $m_{\text{rad}}$ corresponds to the slope of a linear regression between daily insolation and air temperature measurements from the seven official stations with longer-term data records (Figure 1). We calculated $m_{\text{rad}}=0.93$, indicating that a change of 1% in incoming insolation induces an air temperature change of 0.93% (see Data S1 for more details). The clear-sky model is then defined as

$$
\Delta_{\text{clear-sky}} = \Delta_{\text{rad}} \times m_{\text{rad}} \times |T_{\text{flat}}|,
$$

and

$$
T_{\text{clear-sky}} = T_{\text{flat}} + \Delta_{\text{clear-sky}},
$$

where $|T_{\text{flat}}|$ represents the absolute value of air temperature on a flat surface, in our case the output from the lapse-rate model, $\Delta_{\text{clear-sky}}$ the change in air temperature caused by local topography and $T_{\text{clear-sky}}$ the resulting air temperature prediction from the clear-sky model.

2.3.3 | Cloud-corrected model

The cloud-corrected model uses the radiation correction factor to adjust air temperature predictions form the lapse-rate model and thereby also incorporates the effects of cloud cover on local air temperature. Cloud cover can significantly influence incoming insolation. In overcast conditions, for example, incoming insolation is only diffuse; thus, it is independent of terrain slope and aspect and $H_{\text{topo}}=H_{\text{flat}}$. This means that $\Delta_{\text{rad}}$ must tend to one, as cloud cover increases, to account for the increased proportion of diffuse radiation. To include the effects of cloud cover on $\Delta_{\text{rad}}$, the cloud index $c$ was used (Bennie et al., 2008; Schaumberger, 2011),

$$
c = \frac{H_{\text{obs}}-H_{\text{cloud}}}{H_{\text{clear}}-H_{\text{cloud}}},
$$

where $H_{\text{obs}}$ represents the interpolated insolation from the official stations, $H_{\text{clear}}$ the reference maximum insolation in clear-sky conditions and $H_{\text{cloud}}$ the reference minimum insolation in overcast conditions. A cloud index of zero represents overcast conditions and a cloud index of one clear-sky conditions. To calculate $H_{\text{clear}}$ and $H_{\text{cloud}}$, the seven official stations with longer-term records were used (Figure 1). First, the measured maximum and minimum insolation values at these stations were extracted for each month and daily values were calculated by linear
interpolation (Figure S2). Next, all daily maximum and minimum values were averaged across the single stations to calculate a single daily value for $H_{\text{clear}}$ and $H_{\text{cloud}}$, respectively, because they were quite similar for all stations (Figure S2). In contrast, $H_{\text{obs}}$ varied markedly between the stations because of cloud cover differences. To calculate $H_{\text{obs}}$, daily solar insolation from the 15 official stations was interpolated for the whole study area by using ordinary kriging. Finally, daily maps of the cloud index $c$ were calculated at 100 m resolution for the period 2017–2019.

In the next step, the cloud index $c$ was used to calculate the radiation correction factor (Schaumberger, 2011),

$$\delta_{\text{rad}} = c \times \Delta_{\text{rad}} - c,$$

where $\delta_{\text{rad}}$ represents the change in incoming insolation caused by terrain aspect, slope and cloud cover. With increasing cloudiness (small values of $c$), $\delta_{\text{rad}}$ tends towards zero and local differences in incoming insolation weaken. With decreasing cloudiness (high values of $c$), $\delta_{\text{rad}}$ decreases on surfaces with $\Delta_{\text{rad}}<1$, while $\delta_{\text{rad}}$ increases on surfaces with $\Delta_{\text{rad}}>1$. As a result, $\delta_{\text{rad}}<0$ on a surface with low insolation input (e.g., north-exposed slope), and $\delta_{\text{rad}}>0$ on a surface with high insolation input (e.g., south-exposed slope).

Finally, predicted air temperature from the cloud-corrected model can be calculated with the lapse-rate model output, the radiation correction factor $\delta_{\text{rad}}$ and the empirical conversion factor $m_{\text{rad}}$. The cloud-corrected model accounts for changes in air temperature caused by local topography as well as cloud cover and is defined as follows:

$$\Delta_{\text{topo}} = \delta_{\text{rad}} \times m_{\text{rad}} \times |T_{\text{flat}}|,$$

$$T_{\text{topo}} = T_{\text{flat}} + \Delta_{\text{topo}},$$

where $|T_{\text{flat}}|$ represents the absolute value of air temperature on a flat surface, in our case the output from the lapse-rate model $\Delta_{\text{topo}}$ the change in air temperature caused by local topography as well as cloud cover and $T_{\text{topo}}$ the resulting air temperature prediction from the cloud-corrected model.

### 2.4 Cross-validation and statistical comparison

Model performance was assessed by comparing predicted values with measured data from the validation stations through the residuals, the mean absolute error and the prediction bias

$$r_i = \hat{y}_i - y_i,$$

$$\text{MAE} = \frac{\sum_{i=1}^{n}|r_i|}{n},$$

$$\text{Bias} = \frac{\sum_{i=1}^{n}y_i}{n},$$

where $\hat{y}_i$ and $y_i$ represent the model prediction and the measured value for the sample $i$, respectively, $r_i$ the residuals from sample $i$ and $n$ the number of samples.

To determine significant differences between groups of values, we used an analysis of variance (ANOVA) combined with a Tukey test to determine which groups are significantly different from each other. Differences are assumed to be significant if the $p$-value is smaller than .05.

### 2.5 Case study: Grapevine phenology and thermal niche

To further highlight the importance of our approach for agroecological applications, such as phenological simulations and climatic zoning, a phenological model was applied to grapevines. Grapevines were used as target species because accurate reference data were available, which include extensive phenological reference values from the literature and the climate data from the 26 validation stations, all located within vineyards planted with the Pinot noir variety ($Vitis vinifera$ subspecies vinifera). The onset of flowering, veraison and 220 g·L$^{-1}$ sugar content (hereafter ripeness) was predicted with the grapevine flowering veraison model (Parker et al., 2011) and the grapevine sugar ripeness model (Parker et al., 2020). These temperature-based phenological models define the required growing degree days (GDD) to reach specific phenological stages for several grapevine varieties, including Pinot noir. Based on these specifications, we accumulated GDDs at a base temperature of 0°C starting from the 60th day of the year for flowering and veraison and 91st day of the year for ripeness (Parker et al., 2011; 2020) using both, measured temperature from the validation stations and the predicted values from our three models. The day when reaching the threshold GDD value for the respective stage (flowering = 1,219 GDD, veraison = 2,507 GDD, ripeness = 2,933 GDD) was used as the predicted onset day. In a second step, we then characterized the climatic niche for Pinot noir within the present study area based on the previously estimated ripeness day. The ideal window for grape ripeness is often defined as the period
from September 10 to October 10, because temperatures during this period are not too high but still high enough to achieve full ripeness and optimum berry composition (van Leeuwen et al., 2019). In our case, the thermal niche for Pinot noir therefore corresponds to areas where the estimated ripeness stage falls within this ideal window.

### 3 RESULTS

#### 3.1 Model comparison

Table 1 shows the MAE and bias calculated by comparing model predictions with measured data from the validation stations for all three tested models and for each

| Season | MAE (°C) | Bias (°C) |
|--------|----------|-----------|
|        | Lapse-rate | Clear-sky | Cloud-corrected |
|        | Lapse-rate | Clear-sky | Cloud-corrected |
| MAM    | 0.79a      | 0.82a      | 0.72b       |
|        | −0.37a     | 0.19b      | −0.02c      |
| JJA    | 0.61a      | 0.74b      | 0.61a       |
|        | −0.20a     | 0.24b      | 0.09c       |
| SON    | 1.07a      | 1.32b      | 0.90c       |
|        | −0.81a     | 0.48b      | −0.10c      |
| DJF    | 1.71a      | 1.41b      | 1.47c       |
|        | −1.52a     | −0.93b     | −1.17c      |

**Note:** Mean absolute error (MAE) and bias are calculated by comparing model predictions with measured temperature from the validation stations. The three models were compared against each other using a Tukey post hoc test for each season separately. Different letters indicate significant differences between the models (p < .05). MAM = spring, JJA = summer, SON = autumn, DJF = winter.

**TABLE 1** Cross-validation results for the lapse-rate, clear-sky and cloud-corrected models in different seasons

![Model residuals](wileyonlinelibrary.com)

**FIGURE 3** Model residuals during different seasons and cloud conditions. Residuals are defined as predicted minus measured temperature from the validation stations. Cloud index values were extracted at the location of the validation stations for each day. The lines show a linear model between cloud index and residuals for each interpolation method. MAM = spring, JJA = summer, SON = autumn, DJF = winter [Colour figure can be viewed at wileyonlinelibrary.com]
season. The best performance of the lapse-rate model was observed during summer, where the MAE and bias were 0.6°C and −0.2°C, respectively. Throughout the remaining year, the lapse-rate model increasingly underestimated measured air temperature with the worst performance observed during winter (MAE = 1.7°C, bias = −1.5°C). The clear-sky model significantly reduced the MAE over the lapse-rate model during winter by around 17%, but at the same time significantly increased the MAE during summer and autumn by around 20%. In terms of bias, the clear-sky model produced significantly smaller absolute values compared with the lapse-rate model throughout most parts of the year. However, it still underestimated measured air temperature during spring, summer and autumn, with bias values ranging between 0.2 and 0.5°C, and underestimated measured air temperature during winter, where the bias was −0.9°C. The cloud-corrected model outperformed the other two models during spring, summer and autumn and significantly reduced the MAE and bias by 10 and 93%, respectively, compared with the lapse-rate model and by 23 and 90%, respectively, compared with the clear-sky model. In this period, average MAE and bias for the cloud-corrected model were 0.74°C and −0.01°C. During winter, the cloud-corrected model significantly improved the MAE and bias compared with the lapse-rate model, but not compared with the clear-sky model.

Cloud cover had a significant effect on local climate and thus performance of the tested models (Figure 3 and Table S4). The lapse-rate model had the highest accuracy during cloudy conditions (low cloud Index values), but strongly underestimated local air temperature during days with intermediate or no cloud cover (high cloud index values). The clear-sky model, in contrast, had the highest accuracy during clear-sky conditions, where it produced significantly lower absolute residuals than the lapse-rate model and residuals of similar magnitude than the cloud-corrected model, but overestimated local air temperature during overcast and intermediate cloud cover. The cloud-corrected model was the only model that resulted in accurate predictions across all levels of

![Figure 4](https://example.com/figure4.png) **Figure 4** Model residuals during different seasons against elevation of the validation stations. Residuals are defined as predicted minus measured temperature from the validation stations. The lines show a linear model between elevation and residuals for each interpolation method. MAM = spring, JJA = summer, SON = autumn, DJF = winter [Colour figure can be viewed at wileyonlinelibrary.com]
cloudiness, in contrast to the other models that had a high accuracy during either cloudy or clear-sky conditions. During winter, however, residuals of all three models were comparatively high and local air temperature is underestimated across all levels of cloudiness by all three models.

Elevation also had a strong impact on model accuracy with higher elevations characterized by stronger topoclimatic patterns (Figure 4 and Table S5). While air temperature at low-elevation areas (<400 m) was estimated with similar accuracy by all three models, the lapse-rate model progressively underestimated observed air temperature with increasing elevation and residuals decreased to below −1°C at the highest elevations. The clear-sky as well as the cloud-corrected models were both able to strongly reduce this trend. The clear sky model, however, tends to “overcorrect” the air temperature, which led to increased positive residuals, especially during summer and autumn. By accounting also for variable cloud conditions, the cloud-corrected model resulted in significantly smaller absolute residuals during this period. During winter, however, all three models resulted in comparatively high negative residuals across all elevation levels.

3.2 | Examples of daily model results

In the following, characteristics of the cloud-corrected model are illustrated for two example days, representative of winter and summer (Figure 5) and compared to results from the lapse-rate and clear-sky models. Both days included mixed atmospheric conditions, mostly cloudy in the eastern part of the study area and clear in the western part (low and high cloud index values, respectively, Figure 5a). Consequently, $\delta_{rad}$ values of about zero were observed in the east and more extreme values in the west (Figure 5b), indicating weaker and stronger finescale topoclimate variations, respectively. Additionally, $\delta_{rad}$ showed seasonal differences between the summer
day, characterized by $\delta_{\text{rad}}$ values closer to zero, and the winter day, characterized by more extreme values.

Compared with the lapse-rate model, air temperature predicted by the cloud-corrected model included stronger topoclimatic differences with increased values on south-exposed slopes and decreased values on north-exposed slopes. For instance, predicted cloud-corrected air temperature was up to 1°C higher than lapse-rate model predictions on south exposed slopes on the winter day, and up to 1.5°C lower on north exposed slopes on the summer day (Figure 5d). In terms of yearly averages, cloud-corrected air temperature on north- and south-exposed slopes was 1°C lower and 0.8°C higher, respectively, than lapse-rate model predictions. The clear-sky model predicts even stronger topoclimatic differences between north and south exposed slopes than the cloud-corrected model. Air temperature predicted by the clear-sky model was thus higher on south-exposed slopes and lower on north-exposed slopes compared with the cloud-corrected model. During the summer day, for example, air temperature on south-exposed slopes was up to 3°C higher than cloud-corrected predictions, while air temperature on north-exposed slopes was up to 2°C lower.

3.3 | Case study: Grapevine phenology and thermal niche

The cloud-corrected model had the lowest overall MAE and significantly improved the prediction of the phenological stages compared with the lapse-rate model (MAE of 3.35 vs. 5.34 days). The clear-sky model in contrast did not result in a significant improvement over the lapse-
rate model (MAE of 4.37 days). The difference between the three models was especially high on south exposed slopes and increased during the vegetation period (Figure 6). For instance, the difference between the MAE from lapse-rate and cloud-corrected model was 1.5 days for flowering, 2.8 days for veraison and increased to 5.5 days for ripeness (all significant, \( p < .05 \)). The cloud-corrected model also significantly improved phenological predictions compared with the clear-sky model for south-exposed areas up to 900 m, ranging from 1.4 days for flowering up to 2.6 days for ripeness. In contrast, the clear-sky model did not produce a significant reduction for any phenological stage compared with the lapse-rate model.

Because the clear-sky model did not reduce the MAE for the phenological models compared to the lapse-rate model, only the lapse-rate and cloud-corrected models were used to characterize the thermal niche of Pinot noir vines. The simulated niche was highly different between the lapse-rate and cloud-corrected models (Figure 7). The lapse-rate model predicted suitable thermal conditions up to about 1,000 m a.s.l., regardless of aspect and slope. The upper elevation ranges simulated by the cloud-corrected model, in contrast, also show the influence of local topographic conditions. For instance, suitable conditions were predicted up to 1,200 m a.s.l. on very sunny, south-exposed slopes but only up to about 800 m a.s.l. in less favourable conditions.

4 | DISCUSSION

4.1 | Methodological improvements

Our cloud-corrected model accuracy compares well with previous studies, with prediction errors mostly in the range of 0.5–2.0°C (Aalto et al., 2017; Meineri and Hylander, 2017; Macek et al., 2019). However, in contrast to these studies, we were able to consider explicitly the fine-scale climate variability caused by solar radiation and thereby significantly reduced the prediction bias during spring, summer, and autumn (Table 1). Modelling climatic variability at this level of detail was previously difficult (e.g., Meineri and Hylander, 2017), especially in complex topography, and typically required additional field loggers (Greiser et al., 2018; Macek et al., 2019). Moreover, we achieved a higher temporal resolution than similar studies that often use aggregated variables (Greiser et al., 2018; Barton et al., 2019; Macek et al., 2019). Because higher temporal resolution can drastically change predictions of organism responses to climate change, it is extremely important for agricultural as well as ecological applications (Sheldon and Dillon, 2016; Hall and Blackman, 2019; Bütikofer et al., 2020).

Furthermore, we improved on previous studies by including cloud cover dynamics directly into the interpolation process. Until now, most ecological studies had neglected cloud cover dynamics and focused on potential radiation instead (Le Roux et al., 2017; Lenoir et al., 2017; Meineri and Hylander, 2017; Macek et al., 2019). However, our results indicate that local cloud cover is critical for the formation of topoclimate patterns throughout the vegetative period and that significant discrepancies between actual and modelled climate can be introduced if cloud cover is not considered. Similar results were reported by Bennie et al. (2008) and Suggitt et al. (2011), who showed that the radiation effect is weaker in cloudy conditions. Because mountain areas are characterized by a high spatial and seasonal variability of cloud cover (Rottler et al., 2019), the local climate in these regions is particularly sensitive to these dynamics and they should therefore be included in climate models.

Although the spatial resolution of our cloud-corrected model is coarser than most microclimate models (e.g., Maclean et al., 2019), the advantage of our method is the combination of performance and accuracy. The coarser resolution was a necessary compromise to minimize data requirements and computational demand, while still improving on macroclimate models that usually provide results at a scale of several kilometres only. In fact, the direct use of macroclimate variables downscaled to very fine resolutions is a potential limitation for many microclimate models (Kearney et al., 2020), mostly because the climate variability generated by fine-scale topography is not considered by the macroclimate variables (Potter et al., 2013). The method presented in this study explicitly considers topoclimate conditions and can therefore provide valuable input data for microclimate models.

4.2 | Implications for ecological studies in mountain areas

Although our case study example is based on an agricultural crop system, it uses the same principles and methods that are typically used in studies focusing on wild or self-distributing species. For example, grapevine production, despite being clearly influenced by agricultural practices, is strongly linked to very specific climatic site conditions that allow single varieties to fully develop (Fraga et al., 2016; Koufos et al., 2020). The same applies to many wild and self-distributing species and both correlative and mechanistic approaches are therefore usually based on climatic information (Elith and
Leathwick, 2009; Kearney and Porter, 2009). In fact, process-based phenological models have also been used to determine the spatial distribution of European tree species (Duputié et al., 2015), ragweed (Chapman et al., 2014), or insects (Barker et al., 2020). The present approach can therefore provide a useful basis for both crop suitability mapping and for ecological distribution modelling.

Systematic discrepancies between modelled climate and that experienced by organisms are a major source of error when predicting species responses to climate change (Büttikofer et al., 2020). Especially during spring and autumn, when important phenological stages for perennial crops occur (i.e., budbreak, harvest or fruit ripening) accurate information about local temperature is critical to model plant development and distribution (Barnard et al., 2017). Our results show that local climate data are especially important in complex topography with steep and exposed terrain, where temperature estimates based on elevation alone, such as those usually available from macroclimate datasets, do not accurately represent species growing conditions. By considering also solar radiation and cloud cover, our cloud-corrected model was able to strongly reduce systematic differences between observed and predicted temperature during the whole vegetation period and thereby significantly improved our ability to simulate critical stages of plant development in complex mountain topography. Our results also show that reducing such systematic differences is especially important when accumulating model predictions over time, as this can lead to increasing discrepancies between actual and modelled biological responses.

Moreover, our results indicate that topoclimate patterns become more important as elevation increases. This is particularly relevant in the context of climate change, because many species spread into higher elevated areas to avoid increasing temperatures in their original habitat range (Lenoir et al., 2008). In fact, shifts to higher-elevated areas are often considered as important adaptation strategies for agricultural crop systems (van Leeuwen et al., 2019; Santos et al., 2020). However, neglecting local variations in climate conditions strongly affects our ability to characterize the thermal conditions of potentially suitable areas, especially in regions with complex topography. In our case, differences in upper elevation limits for areas with suitable thermal conditions for Pinot noir ripening were as high as 200 m between the lapse-rate and cloud-corrected model. Considering an average lapse-rate of 0.6°C 100 m⁻¹ (Rolland, 2003), this corresponds to a temperature change of 1.2°C, which is of similar magnitude as best-case climate change projections (IPCC, 2021). Accurate fine-scale climate data across different elevation levels is therefore critical to develop effective adaptation strategies.

4.3 Limitations

During winter, the performance of all tested models is strongly limited by the high negative bias from the lapse-rate model, which is most likely related to local meteorological processes, such as cold-air pooling or downslope winds, that occur especially often during winter (Barry, 2008). In the present study, we did not account for such local processes, because this typically requires a higher station density and/or more complex interpolation approaches and thus would make our approach less transferable to other regions. Model comparison in this season should therefore be interpreted with care because the results could be different for other study areas. Our approach could be further refined to provide more robust predictions during winter, for instance by replacing the simple lapse-rate model with more complex approaches, such as nonlinear vertical profiles (Frei, 2014) or topography-based weighted linear regression models (Daly et al., 2002; Crespi et al., 2021) that are better able to simulate the complex and often nonlinear elevation related temperature trend in this season. However, despite this limitation we were able to accurately model topoclimate air temperature throughout the main growing period for most wild and agricultural plants and our approach is therefore still relevant for many agricultural and ecological applications.

Depending on the ecological characteristics of the target species, climate information at a different scale and resolution than presented in this study may be required to get reliable predictors for climate-organism studies (Mod et al., 2016; Lembrechts et al., 2019). For example, air temperature 2 m above ground is in general a weak predictor for growing conditions above the tree line, as most alpine species are strongly influenced by air temperature near the ground surface (Scherrer and Körner, 2011). We therefore focused our analysis on areas below the tree line and on a target species that is well coupled to the surrounding atmosphere, where 2 m air temperature is a good predictor. For high alpine areas, microclimate modelling of air temperature close to the ground surface may provide more reliable climatic information. Such microclimate effects could be included in the present approach, for example, by further downscaling the results of our cloud-corrected model via a microclimate model (Kearney et al., 2020).

The scarce density of observation points is a major challenge for estimating the spatiotemporal variability of cloud cover in mountain areas. This is especially
important at higher elevations, where measurement density is often particularly low. Cloud cover observations from satellites that become increasingly available at higher spatiotemporal resolutions (e.g., Wilson and Jetz, 2016) provide a viable alternative to further improve predictions of local topoclimate at higher elevations. The scarce availability of cloud cover data may also be a limiting factor when calculating topoclimate for future periods. There are some climate models that provide scenarios of future cloud cover dynamics (Vignesh et al., 2020); however, their spatiotemporal resolution still presents a limitation for fine-scale climate models. Until cloud cover scenarios become available at higher spatiotemporal resolution, long-term datasets of high-resolution cloud cover observations (e.g., Wilson and Jetz, 2016) could be used for topoclimate predictions in the near future, where conditions are still comparable to the observed average conditions.

5 | CONCLUSIONS

An accurate spatial description of the local climate is critical to improve our understanding of climate–species relationships. Accurate predictions of species growing conditions in complex mountain terrain strongly depend on our capacity to predict local topoclimate conditions. In this context, it is crucial to consider not only the spatiotemporal resolution at which climate is assessed, but also the variables on which such predictions are based. In this study, we presented a new method to include local topography and climate data in realistic temperature predictions, which not only predicts local air temperature at very high spatiotemporal resolution but also includes important climate forcing factors that are often neglected in climate models, such as solar radiation and cloud cover. The advantage of our method is the combination of performance and accuracy by limiting data requirements while remaining applicable on an ecologically relevant spatial scale. We also provide the R-package “topoclim,” with extensive documentation and example data, allowing scientists to apply this method in future studies. Thus, our flexible and replicable method complements previous lines of research and improves our ability to estimate local climate conditions over complex terrain, especially in regions sensitive to the effects of climate change.

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AUTHOR CONTRIBUTIONS

Simon Tscholl: Conceptualization; data curation; formal analysis; methodology; software; validation; visualization; writing – original draft; writing – review and editing. Erich Tasser: Conceptualization; data curation; methodology; supervision; writing – review and editing. Ulrike Tappeiner: Conceptualization; methodology; project administration; supervision; writing – review and editing. Lukas Egarter Vigl: Conceptualization; data curation; methodology; project administration; resources; supervision; writing – original draft; writing – review and editing.

DATA AVAILABILITY STATEMENT

The data presented in this article, including temperature measurements, modelled solar insolation and validation data, are included in the R-package “topoclim,” available at https://github.com/sitscholl/topoclim. The release relevant to this paper can be found at https://doi.org/10.5281/zenodo.5596291 (Tscholl, 2021).

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