Classification of recent studies by method type for surface air temperature map development and estimation of daily temperature using a radiative cooling scale

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Abstract

Since air temperature maps are essential tools in various fields, there are several studies to estimate surface air temperature at unobserved locations. Air temperature maps have also practical use in a variety of agricultural fields. Practical methods for estimation of surface air temperature are currently not physical but statistical methods. Recent studies on air temperature map development using statistical methods are classified according to method type: (1) rasterizing point data using general techniques for interpolation within computer software such as geographic information systems, i.e., “general rasterization methods”; (2) considering geographical functions based on several factors, i.e., “geographical function methods”; and (3) interpolating anomalies between observation data and long-term normals, i.e., “anomaly methods.” Geographical function or anomaly methods should be more suitable when interpolating current conditions. It is difficult, however, to select a single method, because the most suitable method depends on the area. Practical types of spatial resolution for agriculture are suggested, i.e., high resolution less a few hundred meters, herein called “precise data,” and low resolution greater than that scale, called “coarse data.” Substantial data at specific sites are required for efficient management toward productivity improvement, but current resolutions in agriculture are primarily coarse data. A verified estimation method for surface air temperature, combining statistical and physical techniques, is described as one for acquiring practical and precise data. The method continuously estimates temperature from existing observation data using a new meteorological scale, a radiative cooling scale (RCS). RCS values were calculated using numerical weather prediction model outputs to estimate daily values. Daily temperature at six sites was estimated to have a root-mean-square error of 0.47 K and a mean error of ~0.02 K, validating the values for complex terrain such as hilly areas.

Key words: Air temperature maps, Numerical weather prediction, Precision agriculture, Radiative cooling scale.

1. Introduction

Meteorological data in agriculture are not only important for growers but also for decision makers, such as politicians, administrators, and business people. The World AgroMeteorological Information Service (WAMIS; http://wamis.org/) is the result of various meetings, the Inter-Regional Workshop on Improving Agrometeorological Bulletins held in Bridgetown, Barbados, and an Expert Group Meeting on Internet Applications for Agrometeorological Products held in Washington, DC (organized by the Commission for Agricultural Meteorology). The goal of WAMIS is to make agrometeorological products issued by World Meteorological Organization members available to the global agricultural community on a near-real-time basis. Meteorological maps are the foundation of these agrometeorological products, such as bulletins.
disseminated by WAMIS.

Air temperature maps have practical use in a variety of agricultural fields, such as predicting crop growth and evapotranspiration, assessing water budgets and droughts, and controlling pests and diseases. Desirable air temperatures vary according to subject, i.e., crops, cultivation types, and field geography. There have been various reports on air temperature maps according to user type, use, and objective, and many methods for surface air temperature have been developed. This paper describes a classification of recent studies by method type for surface air temperature data from an existing observatory at designated sites in the past, present, and future. These data may be used to develop air temperature maps.

2. Recent studies on air temperature map development

There are two main methods of estimating air temperature at unobserved locations: a physical method based on numerical models, and a statistical method using data from nearby meteorological stations.

Although numerical models are easily run without large computer resources, computing a large number of factors correlated to air temperature can tax the ability of these resources. Further, output data inevitably include model bias error. Removal of such error for surface air temperature through model improvement alone is very difficult, because surface air temperature is influenced by several factors of terrain and land cover; it is difficult to incorporate all these factors in numerical models, but incorporating some is feasible (Ueyama et al., 2010). The inability of these models to directly simulate features in the boundary layer is problematic when trying to use such outputs directly in a real-world context (Dobrowski et al., 2009).

Current practical methods for estimation of surface air temperature are not physical methods, but statistical ones. These methods are classified into three types: (1) rasterizing observation data using general techniques for interpolation in computer software such as geographic information systems, i.e., “general rasterization methods”; (2) considering geographical functions based on several factors, i.e., “geographical function methods”; and (3) interpolating anomalies between observation data and long-term normals, i.e., “anomaly methods.” The classification does not follow

<table>
<thead>
<tr>
<th>Types of estimation</th>
<th>Techniques</th>
<th>References</th>
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<tr>
<td>General rasterization methods</td>
<td>• Inverse distance weighting</td>
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<td>(rasterizing observation data</td>
<td>• Ordinary kriging</td>
<td>• Thornton et al. (1997) • Dodson and Marks (1997)</td>
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<td>using basic techniques for interpolation)</td>
<td>• Kriging with external drift</td>
<td>• New et al. (1999) • Chuanyan et al. (2005) • Tobin et al. (2011) • Samanta et al. (2012)</td>
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<td>• Splines</td>
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<td>Geographic function methods</td>
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<td>• Seino (1993) • New et al. (2000) • Luzio et al. (2008) • Dobrowski et al. (2009)</td>
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<td>(interpolating anomalies between</td>
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approaches such as inverse-distance weighting (IDW) and multiple regression models. Interpolation techniques are allowed in all classes. A suggested classification is shown in Table 1.

2.1 General rasterization methods

World Agricultural Outlook Board (WAOB; http://www.usda.gov/oce/commodity/) meteorological data were used with the ArcView Spatial Analyst extension to interpolate point values of synoptic and cooperative observer data from the National Oceanic and Atmospheric Administration (Shannon and Motha, 2001). The WAOB is the source of Weekly Weather and Crop Bulletin maps furnished by WAMIS. The maps are developed by the United States Department of Agriculture (USDA) (http://www.usda.gov/oce/weather/pubs/Weekly/Wwcb/index.htm).

Daily Surface Weather and Climatological Summaries (DAYMET) are supported by NASA through the Modeling and Synthesis Thematic Data Center (http://daymet.ornl.gov). DAYMET temperature surfaces are derived using a Gaussian weighting filter and empirically derived relationships (Thronton et al., 1997; Holden et al., 2011a). DAYMET is a model that generates daily surfaces of temperature, precipitation, humidity, and radiation at 1-km spatial resolution, and was developed by the Numerical Terradynamic Simulation Group at the University of Montana.

Dodson and Marks (1997) developed daily minimum and maximum air temperature data with 1-km spatial resolution over large mountainous regions in the US Pacific Northwest. They developed gridded data using an IDW method from neighboring observation data, which were converted to potential sea-level temperature.

New et al. (1999) developed global-mean monthly climatology data with 0.5° latitude-longitude spatial resolution, using thin-plate splines to interpolate observed data.

Chuanyan et al. (2005) developed monthly air temperature data at 30-m spatial resolution to assess potential ecological conditions in the Qilian Mountains of northwest China. They adopted IDW, ordinary kriging (OK), spline, and multiple regression models with four dependent variables, namely, altitude, latitude, longitude, and mean slope gradient. Although they use geographical functions for interpolation, their method is classified as general rasterization, because they reported that the OK model was superior to other methods and that the poorest results were from the spline model.

Guan et al. (2009) developed monthly mean temperature data at 1-km spatial resolution for mountainous regions in Taiwan, using R statistical software with the generalized additive model function of the mgcv package.

Tobin et al. (2011) developed hourly temperature data with 500-m resolution using three methods—IDW, OK, and kriging with external drift (KED)—to analyze measured flood events in the Swiss Alps. They reported that KED with elevation as drift information performed the best.

Samanta et al. (2012) developed monthly and annual air temperature data at 10-min spatial resolution, using the IDW, spline, and kriging methods. They reported that spline interpolation is preferred.

2.2 Geographical function methods

The Japan Meteorological Agency (JMA) developed mesh climatic data of normal values over the preceding 30 years with spatial resolution of 30” latitude×45” longitude. The data were compiled using stepwise multiple regression models with several dependent variables: latitude, longitude, relative relief, land ratio, incline by direction, exposure ratio by direction, and artificial covering ratio (JMA, 2002). Kurihara and Murakami (1982) developed monthly mean temperature data at the same spatial resolution, also using stepwise multiple regression models. Such models have been developed by many researchers to estimate air temperature in complex terrain (Carrega, 1995; Blennow, 1998; Blennow and Persson, 1998; Kanno, 1997; Ohara, 1999; Lookingbill and Urban, 2003; Ueyama, 2004a; Ueyama et al., 2006; Ueyama, 2012).

Meteorological data from the Monitoring Agriculture with Remote Sensing (MARS) Agromet Bulletin for Europe (http://mars.jrc.ec.europa.eu/mars/Bulletins-Publications, disseminated by WAMIS) were interpolated, using average data from up to four stations with a lower score. The set score is calculated using seven factors: average distance between stations and grid centers, average of the absolute difference in altitude ($\Delta_{alt}^{avg}$), weighting factor for $\Delta_{alt}^{avg}$, average absolute difference in corrected distance to the coast, distance between the grid center, and center of gravity of the station set. A technical description is available at
rasterization methods. Daily meteorological data of 25-km spatial resolution for the European Union were taken from the MARS-STAT database provided by the MARS unit of the Institute for Environment and Sustainability of the Joint Research Center of the European Commission (http://mars.jrc.ec.europa.eu/mars/).

Daly et al. (2008) developed climate datasets of 1971-2000 mean monthly precipitation and minimum and maximum temperature at 30° latitude-longitude spatial resolution for the conterminous United States, using the Parameter-elevation Regressions on Independent Slopes Model (PRISM) interpolation method. These data constitute the official spatial climate datasets of the USDA. PRISM calculates a linear climate-elevation relationship, since elevation is the most important factor in distributions of temperature and precipitation. Each station in PRISM is assigned a weight based on eight factors: the cluster, distance, elevation, coastal proximity, topographic facet, vertical layer, topographic position, and effective terrain weights (Daly et al., 2002). PRISM was used to develop the Plant Hardiness Zone Map (http://planthardiness.ars.usda.gov/phz mweb/Default.aspx) of the USDA (Daly et al., 2012). Daly et al. (2007) also developed daily minimum and maximum air temperature data at 50-m spatial resolution using PRISM, for a variety of hydrological and ecological modeling applications in the upper South Santiam Watershed of Oregon, USA.

Ashcroft (2006) developed maximum and minimum air temperature data at 10-m spatial resolution, to plan for issues such as climate change, ecological restoration, and intensified land use. A linear regression model with elevation as a dependent variable was selected for minimum air temperature, and a multiple regression model with elevation and canopy cover as dependent variables was chosen for maximum air temperature.

Models considering cold air accumulation have also been used to estimate minimum air temperature in complex terrain (Chung et al., 2006; Holden et al., 2011b).

Samanta et al. (2012) also modeled temperature using land use, land cover, soil texture, and elevation to improve prediction, in addition to general rasterization methods.

2.3 Anomaly methods

Seino (1993) constructed daily temperature data with 1-km spatial resolution (30° latitude × 45° longitude) using an IDW method. He interpolated anomalies between daily data from neighboring observations and 30-year values such as the mesh climatic data developed by the JMA, converting monthly to daily data using harmonic analysis. His method is standard for developing meteorological maps in Japan.

New et al. (2000) developed monthly air temperature data at 0.5° latitude-longitude spatial resolution by anomaly interpolation, using angular-distance-weighted interpolation. They reported that the surface-fitting procedure using the spline method was generally unsuitable for interpolation of anomaly fields, because of the presence of sharp spatial discontinuities. Mitchell and Jones (2005) constructed a database by efficiently checking inhomogeneities in the station record, for acquiring the station anomaly.

Luzio et al. (2008) constructed daily maximum and minimum air temperature data at 4-km spatial resolution. They interpolated an anomaly-average ratio between the observations and the PRISM climate data, using IDW.

Dobrowski et al. (2009) developed daily temperature (mean, maximum, and minimum) data at 30-m spatial resolution. They formulated data using the anomaly between observations and free-air estimates from the North American Regional Reanalysis of 32-km spatial resolution (Mesinger et al., 2006). Anomaly temperature was estimated using a multiple regression model with elevation, clear sky irradiance, and topographic convergence, with regard to cold-air drainage. Their method does not use normal meteorological data but numerical data instead. Use of numerical data should be dominant in the future.

2.4 Targets according to resolution in agriculture

Estimated data are less reliable when geographical functions are not considered, although general rasterization methods may be applicable to areas with meteorological continuities. Geographical function methods or anomaly methods are more suitable. It is, however, difficult to clearly determine a method, because the most suitable method will vary according to the area. A statistical method with sufficient accuracy in an area would be valid. Nonetheless, practical resolution of meteorological data is not by
area but by objective. The following are suggestions for practical spatial resolutions in agriculture: high resolution less a few hundred meters, herein called “precise data,” and low resolution at larger scales, called “coarse data.” This classification is shown in Table 2.

Coarse data are applicable when there are data to assess meteorological trends, i.e., values relative to other grids or other periods within an area; substantial data at specific sites are not required. Although substantial data might be required for crop models, it is possible to apply coarse data to them. This is because these data that depict the current state with long-term normal values are adequate for these models, since they are not developed based on physical theory but by the use of statistical methods for areas. It is difficult, however, to apply coarse data in statistical models to complex areas such as hilly and mountainous terrain, where there are varied meteorological conditions across the coarse grid. Users of coarse data are classified into three large groups: (1) decision makers in food production management for states, counties, prefectures, and local districts, such as politicians, government officials, and grain dealers; (2) farmers cultivating on plains, where there is less meteorological variation and where crops permitting coarse management (such as rice and wheat) are planted; and (3) researchers or administrators engaged in global issues such as climate change.

Coarse data are predominant in agriculture. Precise data in agriculture have been developed to assess meteorological disasters such as frost damage (Laughin and Kalma, 1987; Blennow and Person, 1998; Takayama et al., 1999; Chung et al., 2006). There is little demand for precise data in major agricultural countries such as the United States and France, because the principal farmlands in these countries are in plains areas, with less meteorological variety. Thus, there has been little practical use for precise data in agriculture. A rare example is the 250-m gridded dataset constructed by Sameshima (2008), used to predict wheat growth in Hokkaido, Japan (Okuno, 2007). Although use of precise data in agriculture is rare, there are certainly suggestions of the importance of such use toward improvement of agricultural productivity, especially in complex terrain such as hilly and mountainous areas and terraced fields (e.g., Kurose, 1991; Ohara, 1999; Evans and Winterhalder, 2000; Ueyama, 2004a, 2004b, 2008a, 2012).

Precise data are more effective than coarse data for management of efficient cultivation, since they can be used as substantial data at designated sites. Such data are effectively applied in the cultivation of specific crops such as citrus fruits, for which it is desirable to manage individual trees (Maotani and Machida, 1977; Cohen and Fuchs, 1987; Pereira et al., 2011), and Japanese tea, about which there is frost damage concern (Suzuki et al., 1982).

### 3. Estimation of daily temperature using a radiative cooling scale

Precise data furnish the potential to realize effective agricultural management. In this endeavor, there are three characteristics required of the data: (1) precise position estimates; (2) substantial data at the sites; and (3) availability of continuous data covering the past, present, and future. In this chapter, an estimation method based on a new idea of Ueyama (2008b), which acquires data satisfying the above characteristics, is described. This method is then used in daily air temperature estimation.

| Table 2. Classification of types of data resolution and users for each objective |
|---------------------------------|---------------------------------|
| Types of data resolution       | User types for each objective   |
| Precise data (less than a few  | • Researchers in ecology and    |
| hundred meters)                | hydrology of mountainous areas  |
|                                | • Technical experts in hilly and |
|                                | mountainous agriculture and     |
|                                | precision agriculture          |
|                                | • Horticulturists growing citrus, tea and similar crops |
| Coarse data (more than several | • Decision makers for food      |
| hundred meters)                | production: politicians,        |
|                                | government officials,           |
|                                | grain dealers and others       |
|                                | • Farmers cultivating land      |
|                                | where crops permit coarse       |
|                                | management, e.g., rice and      |
|                                | wheat                         |
|                                | • Researchers or administrators |
|                                | engaged in global issues       |

H. Ueyama: Recent studies for air temperature and daily estimation using radiative cooling scale
3.1 Development background

For statistical interpolation, observation stations must be located at statistically appropriate sites; strong spatial autocorrelation between observation and estimation sites is required. However, many existing observation sites are too coarsely spaced to ensure statistically reliable air temperature estimates, because the temperature at each site is influenced by the unique local terrain (Yamada, 1995). Meteorological data from existing stations are also unsuitable for estimating the unique local environment at specific sites, because these stations were selected to be representative of conditions in the general area. It is not practical to construct new regular meteorological stations, because of high cost. To address this problem, some researchers have deployed numerous sensors for measuring air temperature across geographically complex terrain (e.g., Blennow, 1998; Ohara, 1999; Lookingbill and Urban, 2003; Ueyama, 2004a; Holden et al., 2011a, 2011b). Such temperature data are not effective for practical use, because they represent temperature over a specific period only (data outside this period are not generally available). Finally, the unique equipment involved makes it difficult to compare the results with other areal temperature studies. Therefore, Ueyama (2008b) developed a new estimation method. This method can estimate air temperature using an existing meteorological network that is too coarse to estimate precise data, but is controlled to a consistent standard.

The essence of the method is to develop estimation models of components constructing the difference in temperature between estimation sites and an existing observation station. These models are developed using a new meteorological scale, a radiative cooling scale (RCS), as a variable, and observation data from simple equipment over a short period. For the past, present, and future at the stations, air temperature at optional sites is acquired without any cost for maintenance or construction of a new observation station. Prediction data are also obtained from a weather prediction model, since its output data can be corrected for an existing station location. The method was used to construct air temperature maps of 50-m spatial resolution in hilly areas (Ueyama, 2008c, 2010, 2012). The data depicted were monthly and 10-day mean air temperature. Estimation of daily air temperature is described below.

3.2 Description of theory

As a starting point in the method, air temperature is converted to potential temperature, because the influence of topographic factors (except altitude) is likely to be underestimated. Values of constants in air pressure computation are derived from a standard atmosphere table. Although air pressure is computed based on a constant lapse rate and mean global sea-level temperature, the effective lapse rate and sea-level temperature are variable when combined in the potential temperature equation. The computed potential temperature is a non-real value. However, the potential temperature difference between an estimation location and existing observation site is used, not actual values alone (Ueyama 2008b).

Air temperature difference is controlled by meteorological conditions such as wind speed and cloud cover (Sumino, 1961; Bootsma 1976; Svesson et al., 2002). Many researchers have reported that air temperature is affected by geographical features surrounding a site (e.g., Tanaka et al., 1983; Laughin and Kalma, 1987; Blennow 1998; Chung et al., 2006). There are different air temperature variations between estimation and permanent observation sites in complex terrain, even under identical weather conditions. Ueyama (2008b) divided differences in potential temperature (∆θ) into two components, an “estimation site component (Tesc)” and a “standard (observation) site component (Tssc)” : Eq. (1). Tesc is computed in Eq. 2 following the procedure of Sumino (1961). He separated air temperature difference from meteorological observation sites into two components, a geographical component and meteorological component, which was determined according to wind speed.

\[ ∆θ = Tesc + Tssc \]  
\[ Tesc = 1/\text{DAYS} \sum_{d=1}^{\text{DAYS}} (∆θd - \overline{∆θd}) \]  

where DAYS is the number of days in the estimation period, \( d \) is an individual day in the period, \( ∆θd \) represents \( ∆θ \) values of each day, and \( \overline{∆θd} \) is the average \( ∆θd \) at all estimation sites.

The distribution of mean air temperature in hilly areas is similar to that of minimum air temperature (Ueyama, 2004a, 2008a). The latter distribution is affected by meteorological conditions, and minimum
air temperature is related to radiative cooling intensity (Bootsma, 1976; Laughin and Kalma, 1987). Estimation models for $T_{esc}$ and $T_{ssc}$ were then formulated using a variable representing this intensity.

An $RCS$ was proposed as a new meteorological scale by Ueyama (2008b). This scale is defined as the difference in potential temperature between an upper pressure surface and ground surface: Eq. (3). Values of $RCS$ greater than zero indicate development of a surface-inversion layer and greater radiative cooling. The $RCS$ is dimensionless, although it is defined as a potential temperature difference. This is because a specific value at the upper pressure surface would be meaningless in representing meteorological situations in an estimation area (Ueyama, 2008b). The $RCS$ is not a numerical value directly representing radiative cooling intensity at the ground surface. Instead, it is a scale representing meteorological conditions such as cloud amount and wind speed across the entire estimation area, which are correlated with stronger or weaker radiative cooling. Hence, the upper pressure surface varies with topography when $RCS$ values are determined.

$$RCS = \theta - \theta_G$$

where $\theta$ is the potential temperature at the upper level of the observation site and $\theta_G$ is the potential temperature at the ground level.

Ueyama (2008b) found that the two components $T_{esc}$ and $T_{ssc}$ representing the difference in potential temperature are formulated by linear correlation, with the $RCS$ as an independent variable. This phenomenon was verified by analysis using two datasets: (1) multiyear data from existing stations, acknowledging the influence of spatially variable weather conditions related to coarse spacing of selected stations; and (2) fine spatial data from a dense array of manual observation equipment (which did not record multiyear data).

### 3.3 Estimation method for daily temperature

Reliable daily $RCS$ values could not be acquired in past studies (Ueyama, 2008b, 2008c, 2012). $RCS$ values were acquired using statistical models developed from rawinsonde and ground-based data on wind speed, air temperature, and sunshine duration, because values were required for areas in which there was no rawinsonde observation. The estimation accuracy of daily data is worse than that of monthly or 10-day mean data when $RCS$ values are determined using statistical models. Here, these values were determined using daily potential temperature at an upper level from numerical model output, because numerical model predictions are more reliable for upper temperature than for surface air temperature.

In Japan, the JMA began operational runs of a mesoscale model (MSM) at 10-km resolution (Saito et al., 2006) in March 2001, for which 18-h time integration was performed four times per day. Resolution was enhanced to 5 km in March 2006, and the model was run on a 3-hourly basis (eight times per day). The forecast time was extended to 33 h in March 2007. These MSM-run extensions were in accord with initial and boundary condition changes at the JMA to the global spectral model (GSM) of 20-km resolution (Nakagawa, 2005; JMA, 2007). MSM outputs are offered as grid point value (GPV) data by the Japan Meteorological Business Support Center. The MSM was used to determine $RCS$ values. Upper-level potential temperature was computed using the GPV of the four grids nearest an Automated Meteorological Data Acquisition System (AMeDAS) site, using IDW.

To obtain data for $T_{esc}$ and $T_{ssc}$, self-assembled
observation equipment was deployed to measure air temperature at six estimation sites, and an AMeDAS station was used as the standard site. It was located in a hilly area of northeast Hiroshima Prefecture (Fig. 1). Air temperature data used for construction of the estimation models were recorded during February 1-10 and May 1-10, 2008. Temperature data for validation were collected during August 21-31 and September 1-10, 2008.

The observation equipment in Hiroshima Prefecture consisted of a small thermometer (ESPEC, Thermo Recorder Mini RT-30S) within a heat insulation material (urethane foam) and polypropylene, and a mounted solar ventilator (IPC, SolarVENT 24AE) for air circulation surrounding the thermometer. When compared with values measured by a platinum resistance thermometer (EKO, PT100Ω 4-wire), this system measured daily air temperature with a root-mean-square error (RMSE) of 0.12 °C. Measured values from both thermometers were corrected for instrumental error. Each instrumental error was calculated from measured data in a thermostatic chamber. The RMSE between the AMeDAS values and those measured by the self-assembled observation equipment was 0.27 °C. The RMSE difference between the platinum resistance thermometer and AMeDAS was a result of their unique instrumental errors and a difference in observation procedure. Air temperature for AMeDAS was sampled every 10 seconds and data recorded as 10-min mean values, and air temperature for the self-assembled equipment was recorded and data sampled every five minutes.

Although Ueyama (2008b) developed mean air temperature estimation models for a given time period, the aim here was to develop an estimation model of daily air temperature. $T_{esc}$ is thus calculated using

$$T_{esc} = \Delta \theta - \bar{\Delta \theta}$$

where $\Delta \bar{\theta}$ is the mean of $\Delta \theta$ for all estimation sites.

### 3.4 Results and discussion

The 925-hPa surface was used for GPVs of upper-level potential temperature, because it was above the altitude (510 m) of the AMeDAS site but was the nearest surface to this site. Although there are GPV ground surface data, AMeDAS data were used for potential temperature at ground level. This is because GPVs are theoretical values computed by the model, which causes the potential temperature difference between an upper pressure surface and the ground surface to be nearly zero.

Figure 2 shows the relationship between $RCS$ and $T_{ssc}$ values during 1-10 February and 1-10 May.

![Fig. 2. $T_{ssc}$ versus $RCS$ values during 1-10 February and 1-10 May.](image)

![Fig. 3. Comparison of observed and estimated $T_{ssc}$ values during 21-31 August and 1-10 September.](image)

**Table 3.** Estimation models of $T_{esc}$ values at each site, constructed from data recorded during 1-10 February and 1-10 May

<table>
<thead>
<tr>
<th>Sites</th>
<th>Models</th>
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<tbody>
<tr>
<td>1</td>
<td>$T_{esc} = +0.209 \cdot RCS + 1.017$</td>
</tr>
<tr>
<td>2</td>
<td>$T_{esc} = -0.056 \cdot RCS + 0.178$</td>
</tr>
<tr>
<td>3</td>
<td>$T_{esc} = -0.078 \cdot RCS - 0.881$</td>
</tr>
<tr>
<td>4</td>
<td>$T_{esc} = -0.004 \cdot RCS + 0.044$</td>
</tr>
<tr>
<td>5</td>
<td>$T_{esc} = -0.114 \cdot RCS - 0.580$</td>
</tr>
<tr>
<td>6</td>
<td>$T_{esc} = +0.003 \cdot RCS + 0.343$</td>
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</table>
Tssc values in the observation data from February 1-10 and May 1-10, 2008. There is a linear correlation between daily Tssc and RCS values; \( Tssc = 0.0799 \cdot RCS + 0.183 \). This result is similar to Ueyama’s (2008b). The validation results for the Tssc estimation model are shown in Fig. 3. This model, which was developed from observation data, had an RMSE of 0.22 K. Because of this acceptable RMSE value and a mean error (ME) approaching zero, the model for Tssc should be suitable.

There was a linear correlation between RCS and Tesc values from the observation. Tesc models constructed using observation data from February 1-10 and May 1-10, 2008 are shown in Table 3. Negative slopes were output by the models for sites that become significantly colder at night, such as those on valley floors or within topographic basins. Positive slopes were output for sites with mild nighttime temperatures, such as hilltops or upper-hill slopes. For example, Fig. 4 shows the relationship between Tesc and RCS for sites on such slopes (No. 1) and on valley floors (No. 5). These results are similar to Ueyama’s (2008b). The validation results for the Tesc estimation model are shown in Fig. 5. The estimation model for Tesc developed from the observation data gave an RMSE of 0.43 K. This RMSE and a ME approaching zero again indicate the suitability of the model.

Figure 6 shows the relationship of \( \Delta \theta \) values between observation and estimation, from estimated Tssc and Tesc. Differences between the AMeDAS and each estimation site showed an RMSE of 0.47 K and an ME -0.02 K, which again suggest the suitability of the model. Therefore, the method of Ueyama (2008b), using RCS values from a physical model, estimates daily potential temperature with allowable accuracy. Daily air temperature based on AMeDAS was estimated at each site by converting potential temperature to air temperature, using site elevation data.

A 20-day observation period for the two models developing Tesc and Tssc may be too short to construct adequate models. In Ueyama’s method, it is not important to observe data over a long period, but it is essential to have adequate RCS magnitudes. These magnitudes during the observation period (-5 to 15) were not small in comparison with other results. The estimation models for \( \Delta \theta \) should therefore be adequate.

It was verified that Ueyama’s (2008b) method
estimates daily potential temperature difference based on AMeDAS, using RCS values determined by a numerical model. The results of this study suggest that air temperature prediction at designated sites in complex terrain can be achieved based on the air temperature product GUIDANCE, i.e., corrected GPV values from the GSM at each AMeDAS site by the JMA.

4. Conclusion

Recent studies on surface air temperature map development were classified by method type. The best method with suitable spatial resolution varies according to the objective and features in an area. However, geographical function or anomaly methods should be more suitable, although general rasterization methods may be applicable to areas with meteorological continuity. Although coarse data are important in agriculture, estimation methods for substantial data applied as actual site data are required in order to realize efficient management for productivity improvement.

An estimation method using an RCS proposed by Ueyama (2008b) was illustrated and then applied to daily air temperature estimation. The method estimates daily potential temperature with allowable accuracy. It combines statistical and physical modeling techniques, and is potentially feasible for achieving effective management of agricultural cultivation in specific situations, e.g., hilly and mountainous areas, terraced fields, sloping orchards, and tea fields.

Weather prediction techniques using numerical models will be further developed. However, it is difficult to directly apply data from these models to agriculture. This is because data from such models, which are based on dynamics between the global atmosphere and ocean, are insufficiently accurate in real situations. Furthermore, the spatial scale of numerical model outputs tends to be much larger than those of ground-level measurements. Methods combining statistical and physical techniques will be useful in meteorological map development for agriculture.

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