5.6 Guidance for Short-range Forecasting

5.6.1 Overview

To assist forecasters in issuing quantitative weather forecasts, various kinds of forecast guidance products are calculated from the output of the NWP models. The parameters of the guidance for short-range (up to 75 hours) forecasting are listed in Table 5.6.1.

The first objective of the guidance is to reduce forecast errors, mainly bias errors, of NWP output such as temperature. The second objective is to derive quantitative values of parameters not directly calculated in the NWP models, such as probability of precipitation.

Table 5.6.1 Parameters of guidance products for short-range forecasting.

Parameters	Target	Model	Forecast hour	Method**
Categorized weather over 3(6)hours (fair, cloudy, rainy, sleety, snowy)	Grids (20km)	RSM	KT= 3-6, 6-9,……, 48-51	NRN
		GSM	KT= 51-57,………, 69-75	
Mean precipitation amount over 3(6)hours	Grids (20km)	RSM	KT= 3-6, 6-9,……, 48-51	KF
		GSM	KT= 51-57,………, 69-75	
		MSM	KT=0-3, 3-6, 6-9,9-12,12-15	
Maximum precipitation amount over 1,3 and 24(only RSM) hours	Warning area	RSM	KT= 3-6, 6-9,……, 48-51	KF &
		MSM	KT=0-3, 3-6, 6-9,9-12,12-15	NRN
Probability of precipitation over 6 hours > 1mm/6h	Grids (20km)	RSM	KT= 3-9, 9-15, …., 45-51	KF
		GSM	KT= 51-57,………, 69-75	
Maximum temperature in the daytime (09-18 local time)	AMeDAS points	RSM	Today and Tomorrow	KF
		GSM	Day after tomorrow	
Minimum temperature in the morning (00-09 local time)	AMeDAS Points	RSM	Today and Tomorrow	KF
		GSM	Day after tomorrow	
Time-series Temperature	AMeDAS points	RSM	FT= 3, 6, 9, 12,…….48,51	KF
		GSM	FT= 54, 60, 66, 72	
Wind speed and direction	AMeDAS points	RSM	FT=3 , 6, 9, 12,…….48, 51	KF
		GSM	FT= 54, 60, 66, 72	
Maximum wind speed and direction over 3hours	AMeDAS points	MSM	KT=0-3,3-6,6-9,9-12,12-15	KF
		RSM	KT=3-6, 6-9,…….48-51	
Daily minimum humidity	SYNOP points	RSM	Today and Tomorrow	NRN
		GSM	Day after tomorrow	
Probability of heavy precipitation over 3 hours > 30mm/3h (warm season) > 20mm/3h (cold season)	Grids (40km)*	RSM	KT= 3-6, 6-9,……, 48-51	NRN
Snow-to-Liquid-equivalent Ratio over 3hours	Grids (20km)	RSM	KT= 3-6, 6-9,……, 48-51	NRN
Snowfall amount over 12 hours	Selected AMeDAS points	RSM	KT= 12-24, 24-36,36-48	NRN
		GSM	KT=48-60,60-72	
Probability of thunderstorm over 3 hours	Grids (20km)*	RSM	KT= 3-6, 6-9,……, 48-51	NRN
		MSM	KT=3-6, 6-9,9-12,12-15	LR

* Disseminated values are the maximum in the grids belonging to each local meteorological observatory's area of responsibility.

** KF: Kalman Filter, NRN: Neural Network, LR: Logistic Regression

To cope with frequent model upgrades, JMA developed methods of adaptively correcting the statistics of the relationship between NWP output and the corresponding observation. The methods, based on Kalman Filter and Neural Network, were put into operational use for the first time in 1996. Since then the adaptive methods have been applied to all of the parameters, replacing the formerly used non-adaptive multivariate regression method.

In the following subsections, Kalman Filter and Neural Network used in the guidance system are explained in 5.6.2 and 5.6.3, respectively, and the utilization of the guidance in forecasting offices is summarized in 5.6.4.

5.6.2 Guidance by Kalman Filter

(a) Kalman Filter

Kalman Filter (KF) as a statistical post-processing method of NWP output was developed in JMA on the basis of earlier works of Persson(1991) and Simonsen(1991). The notation of KF, which basically follows that of Persson(1991), is as follows:

- y : predictand (target of forecast)
- $\boldsymbol{c}$: predictors (1 × n matrix)
- $\boldsymbol{X}$: coefficients (n × 1 matrix)
- $\boldsymbol{Q}$: covariance of $\boldsymbol{X}$ (n × n matrix)
- τ : sequence number of NWP initial times

First, the observation equation, which is a linear model for relating the predictand with pre-selected predictors, and the system equation are given as:

$$y_\tau = \boldsymbol{c}_\tau \boldsymbol{X}_\tau + v_\tau \tag{5.6.1}$$

$$\boldsymbol{X}_{\tau+1} = \boldsymbol{A}_\tau \boldsymbol{X}_\tau + \boldsymbol{u}_\tau \tag{5.6.2}$$

where v_τ is the observational random error whose variance is D_τ, and $\boldsymbol{u}_\tau$ is the random error vector of the system whose covariance matrix is $\boldsymbol{U}_\tau$. The matrix $\boldsymbol{A}_\tau$ describes the evolution of the coefficients in time and is set to the unit matrix in this case;

$$\boldsymbol{A}_\tau \equiv \boldsymbol{I} \tag{5.6.3}$$

The objective of KF is to obtain the most likely estimation of the coefficients $\boldsymbol{X}_{\tau+1/\tau}$, whose subscripts denote that this is estimated using the observation corresponding to the forecast at τ and used for the prediction at $\tau+1$. In contrast, single subscripts in eqs. (5.6.1-2) denote the "true" values at τ. $\boldsymbol{X}_{\tau+1/\tau}$ is obtained from the previous estimate $\boldsymbol{X}_{\tau/\tau-1}$ and the forecast error:

$$\boldsymbol{X}_{\tau+1/\tau} = \boldsymbol{X}_{\tau/\tau} \tag{5.6.4}$$
$$= \boldsymbol{X}_{\tau/\tau-1} + \boldsymbol{\delta}_{\tau}(\mathrm{y}_{\tau} - \boldsymbol{c}_{\tau}\boldsymbol{X}_{\tau/\tau-1}) \tag{5.6.5}$$

where

$$\boldsymbol{\delta}_{\tau} = \boldsymbol{Q}_{\tau/\tau-1}\boldsymbol{c}_{\tau}^{\mathrm{T}}(\boldsymbol{c}_{\tau}\,\boldsymbol{Q}_{\tau/\tau-1}\,\boldsymbol{c}_{\tau}^{\mathrm{T}} + \mathrm{D}_{\tau})^{-1} \tag{5.6.6}$$

$\boldsymbol{Q}$, the covariance of $\boldsymbol{X}$, is updated as follows:

$$\boldsymbol{Q}_{\tau+1/\tau} = \boldsymbol{Q}_{\tau/\tau} + \boldsymbol{U}_{\tau} \tag{5.6.7}$$
$$= \boldsymbol{Q}_{\tau/\tau-1} - \boldsymbol{\delta}_{\tau}\boldsymbol{c}_{\tau}\,\boldsymbol{Q}_{\tau/\tau-1} + \boldsymbol{U}_{\tau} \tag{5.6.8}$$

Equations (5.6.4) and (5.6.7) are derived from (5.6.2)-(5.6.3).

Finally, the forecast value is calculated with the updated coefficients and predictors at $\tau+1$;

$$y_{\tau+1/\tau} = \boldsymbol{c}_{\tau+1}\boldsymbol{X}_{\tau+1/\tau} \tag{5.6.9}$$

For some forecast parameters, temperature for example, the predictand y is the difference between the NWP output and the observation, while for the others, precipitation amount for example, y is the observation itself. In the case of wind, u and v components are treated simultaneously with the predictand y as a complex number.

In the forecast guidance system with KF, D_{τ} and $\boldsymbol{U}_{\tau}$ in eqs. (5.6.6) and (5.6.8), respectively, are treated as empirical parameters of controlling the adaptation speed.

(b) Frequency bias correction

With KF, the most likely estimation of the predictand which minimizes the expected root-mean-square error is obtained. However, the output has a tendency of lower frequency of forecasting rare events, such as strong wind or heavy rain, than the actual. To compensate this unfavorable feature, a frequency bias correction scheme is applied to the KF output of some parameters.

The basic idea is to multiply the estimation of KF, y, by a correction factor $F(y)$ to get the final output y^{b}:

$$y^{\mathrm{b}} = y \cdot F(y)$$

To determine $F(y)$, a number of thresholds t^{i} are fixed so that the forecast frequency over them should be approximating to that of observation. The objective of the scheme, then, is to find f^{i} corresponding to each t^{i} that determines the correction factor as follows:

$$F(f^{i}) = t^{i} / f^{i}$$

$F(y)$ for $f^{i} < y < f^{i+1}$ is linearly interpolated between $F(f^{i})$ and $F(f^{i+1})$.

Since KF is an adaptive method, f^{i} is also updated each time the observation y_{τ} corresponding to the estimates of KF $y_{\tau/\tau-1}$ is available. The update procedure is as follows:

$$f^{i}_{\tau+1} = \begin{cases} f^{i}_{\tau}(1+\alpha) & \text{if } y_{\tau} < t^{i} \text{ and } y_{\tau/\tau-1} > f^{i} \\ f^{i}_{\tau}(1-\alpha) & \text{if } y_{\tau} > t^{i} \text{ and } y_{\tau/\tau-1} < f^{i} \\ f^{i}_{\tau} & \text{otherwise} \end{cases}$$

where α is an empirical parameter to determine the adaptation speed.
This frequency bias correction is applied to the guidance for wind and precipitation amount.

(c) An example of the guidance by Kalman Filter (3-hour precipitation amount)

In this guidance, the predictand is the observed 3-hour accumulated precipitation amount averaged within a 20km x 20km square, and the following nine parameters derived from RSM output are used as predictors.

(i) NW85 : NW-SE component of wind speed at 850hPa
(ii) NE85 : NE-SW component of wind speed at 850hPa
(iii) SSI : Showalter's stability index
(iv) OGES : Orographic precipitation index
(v) PCWV : Precipitable water contents × wind speed at 850hPa × ascending speed at 850hPa
(vi) QWX : Σ (Specific humidity × ascending speed × relative humidity) between 1000 and 300hPa
(vii) EHQ : Σ (Depth of wet layer × specific humidity) between 1000 and 300hPa
(viii) DXQV : Precipitation index on winter synoptic pattern
(ix) FRR : Precipitation by the model (RSM)

Figure 5.6.1 is an example of precipitation forecasts. The observation (A) shows that there was no precipitation in the area M, where the model (C) predicted precipitation whose maximum was over 5 mm/3h. On the other hand, the guidance (B) predicted much less precipitation than the model, showing better results. Examination of the coefficient values at point P revealed that the coefficient of EHQ was the largest and four times as large as that of FRR.

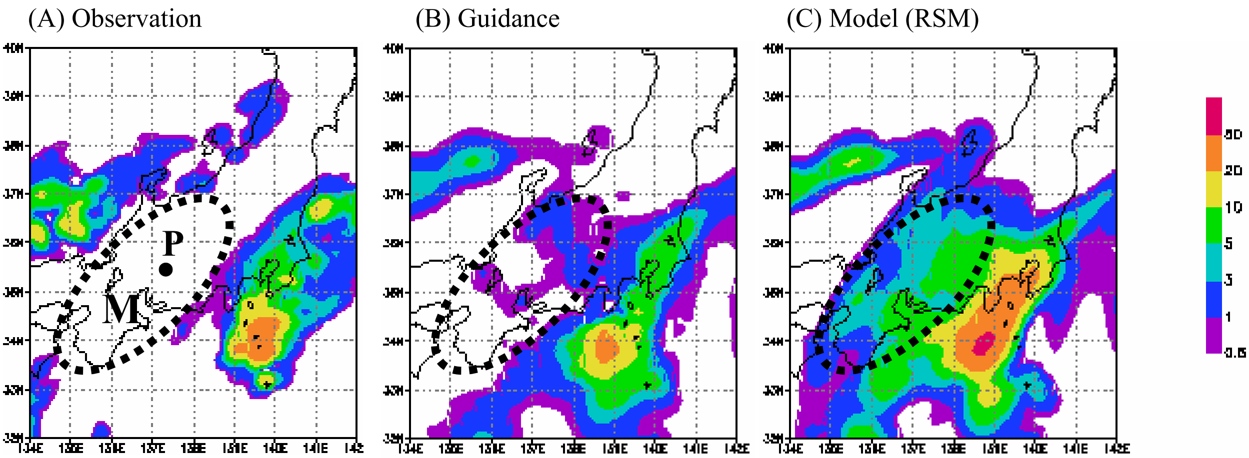

Fig. 5.6.1 Mean precipitation amount over 3 hours. (A) Observation. (B) Forecast by the guidance. (C) Forecast by the model (RSM).

5.6.3 Guidance by Neural Network

(a) Neural Network

The Neural Network (NRN) is one of the artificial intelligence methods and is an effective technique to analyze non-linear phenomena. Its basic element is called a "neuron", and multiple neurons are linked together to construct a hierarchical neural network, as shown in Fig. 5.6.5. The first layer is called the "input layer", the last layer is called the "output layer", and the layers between them are called "hidden layers".

When a signal is put into the input layer, it is propagated to the next layer through the interconnections between the neurons. Simple processing is performed on this signal by the neurons of the receiving layer prior to its being propagated on to the next layer. This process is repeated until the signal reaches the output layer.

A schematic diagram of a neuron is shown in Fig. 5.6.2. The input of each neuron is a weighted sum of the outputs of other neurons, and the output is a function of its input. This function is called an "activation function", and a sigmoid function shown in Fig. 5.6.3 is usually used.

The weights of NRN are iteratively adjusted through learning numerous sets of input/output data. The most popular way to adjust weights is the "back propagation of error" algorithm described as follows:

(i) At first, weights are initialized with randomized values.

(ii) The NRN gets a set of input values and calculates output.

(iii) The weights are adjusted to make the NRN output approach the "supervisor data" (correct values of the output variable).

(iv) Processes of (ii) and (iii) are iterated until the error measure falls below a specified value or a specified maximum number of iterations is reached.

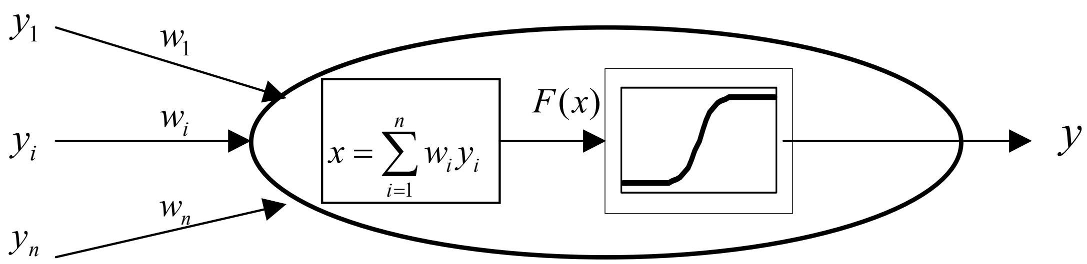

Fig. 5.6.2 A schematic diagram of a neuron.

$$F(x) = \frac{1}{1 + e^{-(2/c)x}}$$

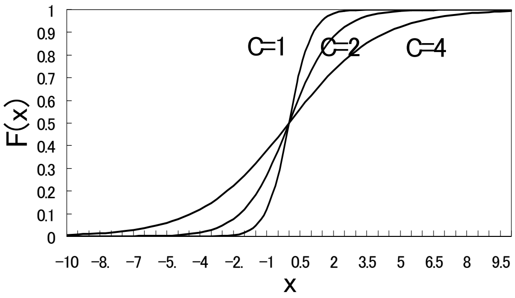

Fig. 5.6.3 Examples of sigmoid function.

(b) An example of the guidance by Neural Network (Categorized weather)

In the forecast guidance system, a Neural Network model is constructed at each grid or observation point from the sets of NWP output and observed weather elements. Categorized weather is one of the forecast guidance parameters to which NRN is applied. Figure 5.6.4 shows an output example of categorized weather guidance. In this guidance, a NRN model is used to derive sunshine duration, which is used to determine the non-precipitating weather categories (fair or cloudy). The NRN is constructed at each AMeDAS station, and output values (3-hourly sunshine duration) are interpolated to grid points. The precipitating weather categories (rain, sleet, snow) are determined from the KF-based precipitation amount guidance described in 5.6.2 and another NRN. The constitution of the sunshine duration NRN model is shown in Fig. 5.6.5, and its characteristics are summarized as follows:

(i) It is a 3-layered Back Propagation Network.

(ii) As an activation function of each neuron, a linear function is used in the input and output layer, and a sigmoid function is used in the hidden layer.

(iii) In learning processes, NWP output is used as input data, and sunshine duration observed at each AMeDAS point is used as supervisor data.

(iv) The weights of the network are modified at every time when the observation corresponding to the forecast is obtained.

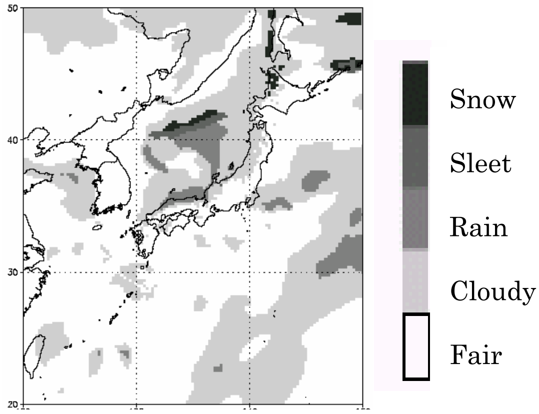

Fig. 5.6.4　An example of output of the categorized weather guidance

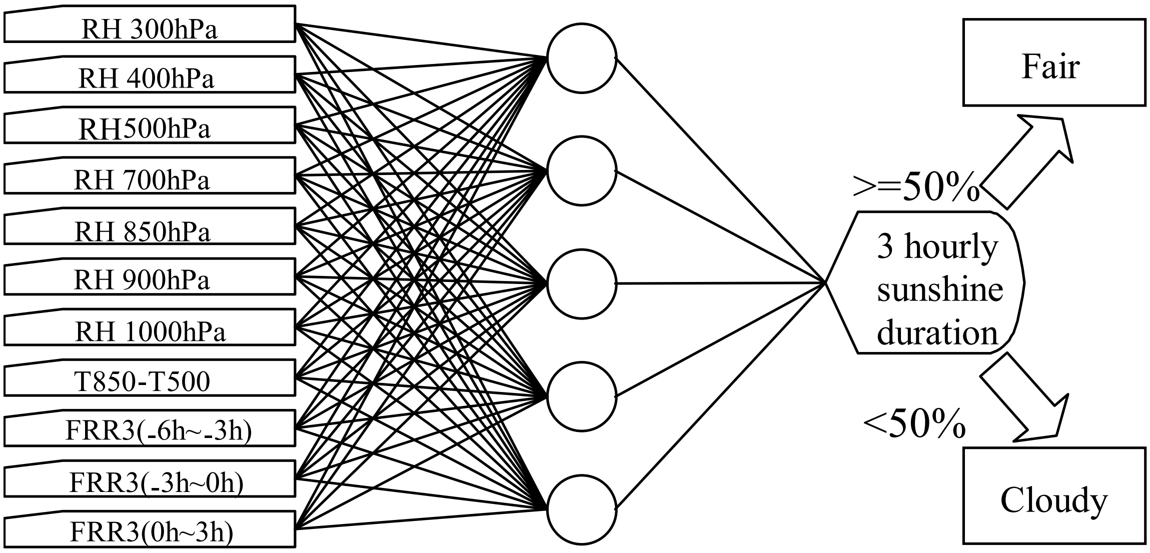

Fig. 5.6.5　Neural Network for fair / cloudy determination.

RH: Relative humidity,　FRR3: Precipitation over 3 hours

5.6.4　Utilization of the guidance in forecasting offices

The forecast guidance products are disseminated to forecasting offices and used as inputs to the forecast editor. Figure 5.6.6 shows an example of its input window. The forecaster revises elements (categorized weather, PoP, temperature etc.) on the display when it's considered to be necessary from current weather condition or empirical knowledge. Then, the forecast bulletin is composed and disseminated to the users.

To make a draft of the weather forecast bulletin automatically, an algorithm shown bellow is used:

(i) 3-hourly dominant weather categories (Fig. 5.6.6 second line) are derived from the majority of the categorized weather on the grids in the forecast area .

(ii) The draft of the weather forecast bulletin for a day (Fig. 5.6.6 middle) is derived from the sequence of 3-hourly dominant weather categories over the forecast area. Some examples of the algorithm are shown in Table 5.6.2.

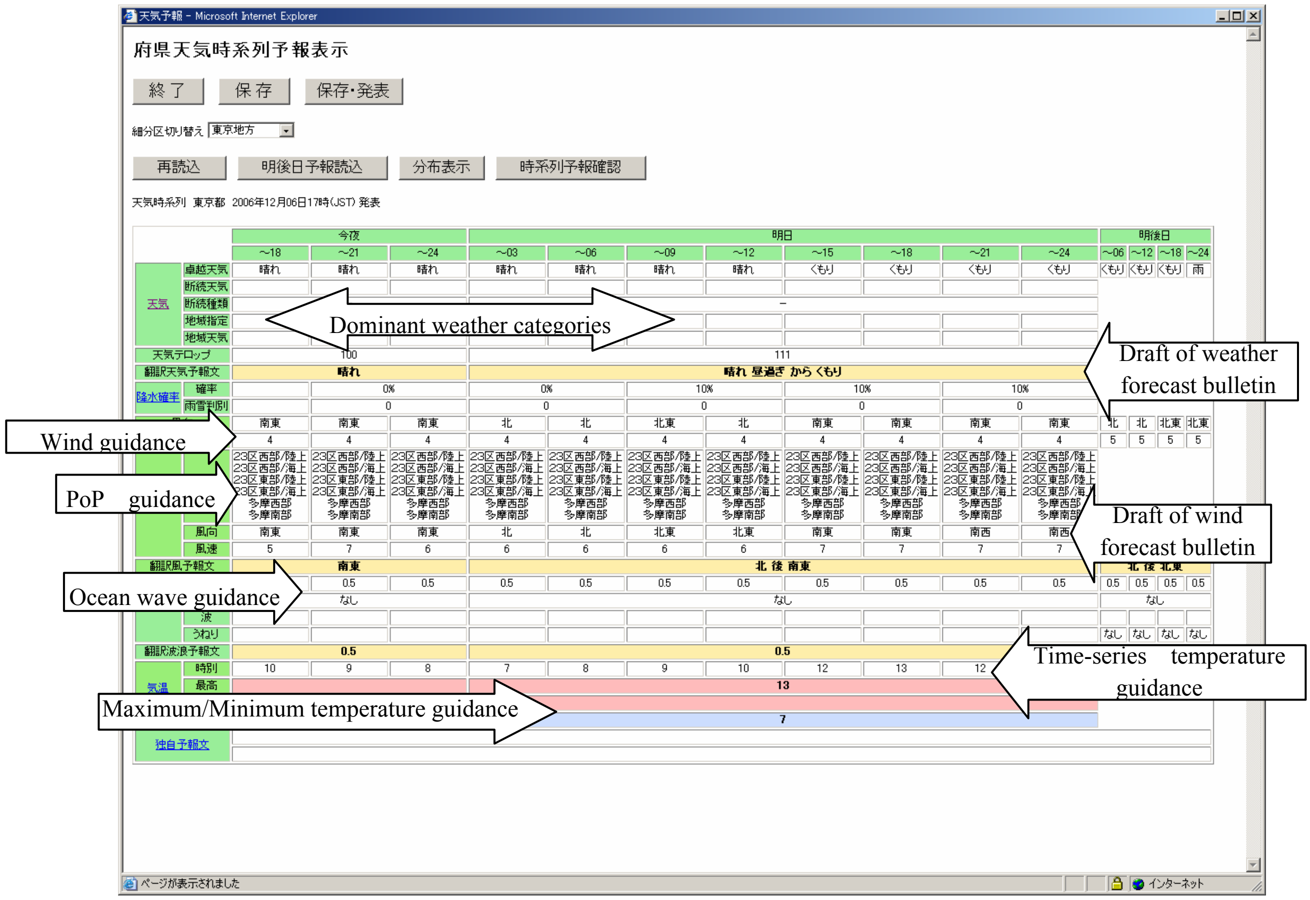

Fig. 5.6.6 An example of an input window of the forecast editor.

Table 5.6.2 Examples of the algorithm for making a draft of the weather forecast bulletin

Sequence of 3 hourly categorized weather*	Draft of a weather forecast bulletin
FFFFCFFF	Fair
RRRRRSSS	Rain, snow from the evening
CRFRCFRC	Cloudy, occasional rain
CRCCCCRC	Cloudy, rain in the morning and the evening

* F:Fair C:Cloudy R:Rain S:Snow

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