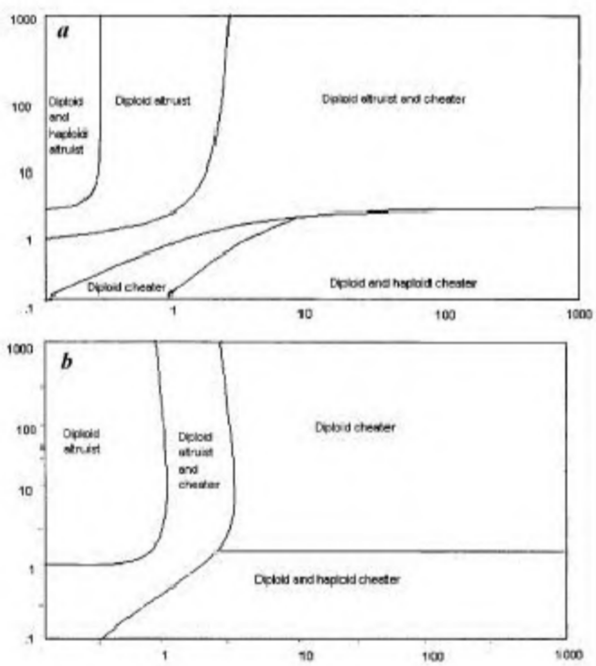

Figure 3. Parameter space (denoting group benefit of cooperation on the x-axis and individual benefit of cheating on the y-axis) over which different genotypes evolve in the third model. ***a***, Altruist allele dominant and ***b***, cheater allele dominant. Like the second model, the patterns are similar in both altruist and cheater dominant cases, although the underlying mechanisms are different.

and (ii) among organisms which have diploid and haploid stages in their life cycle, cooperation should be more common in the diploid stages than the haploid ones. Just a few examples of altruism, cooperation or eusociality are known among predominantly asexual taxa, particularly prokaryotes. The renewed interest in the social life of microorganisms might bring out a number of novel examples of cooperation in bacteria[13]. At this stage, therefore, the available data are inadequate to test the first prediction quantitatively. Among the well-known examples of sociality in microorganisms are fruiting body formation in Myxobacteria and slime moulds. In both the examples, cheaters have been shown to occur frequently in natural populations (Watve, M. G., unpublished)[1–3]. Sexual reproduction is not known in Myxobacteria, but is known to occur in *Dictyostelium*[14]. Studies on sexual reproduction in *Dictyostelium* are scanty, but apparently the ratio of cells sacrificed per spore produced is much larger in sexual spore formation compared to asexual spore formation[14]. In basidiomycetes and ascomycetes, more complex stages showing a greater degree of division of labour among cells and a greater proportion of sterile cells are diploid and the simpler stages haploid. These examples fit well into the predictions of the model, qualitatively. It is difficult to test the prediction quantitatively with available data. However, the picture in hymenopterans is clearcut, in that all cooperative stages are necessarily diploid, while no haploid stage is known to cooperate.

Another speculation arising out of the model is that primitive multicellularity might have been similar to that seen in cellular slime moulds, where polyclonal cooperation could be inevitable. This might have been the right situation for sex and cooperation to coevolve leading to an association between multicellularity and sex. Such an association might have persisted in spite of the nature of multicellularity as well as that of sex changing in the course of evolution. As a result, the unicellular taxa are predominantly asexual and the multicellular ones have a large proportion of sexually reproducing species.

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Fuzzy rule-based system for prediction of direct action avalanches

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Rule-based systems are widely being used in decision making, control systems and forecasting. In the real world much of the knowledge is imprecise, uncertain, ambiguous and inexact in nature. Fuzzy logic offers a better way to represent complicated situations in terms of simple natural language.

Here an attempt has been made to develop a rule-base for prediction of direct action avalanches of Chowkibal–Tangdhar road axis (Jammu and Kashmir) in Indian Himalaya using fuzzy logic. The condition

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attributes of the rule-based system are six snow-related parameters selected from the past dataset of the representative observatory 'Stage-II' in the axis. Different fuzzy sets are defined for each parameter on the basis of their distribution with four danger labels of avalanche activity.

A total of 101 composite rules are developed for different danger labels of avalanche activity. The results show good agreement with the danger classification for avalanche activity and prediction of non-avalanche activities.

THE predominantly used methods for forecasting avalanche hazards are conventional techniques and statistical methods, such as contributory factor analysis and nearest neighbourhood techniques[1]. Operational avalanche forecasting based on the above methods is widely practised worldwide. In India, Snow and Avalanche Study Establishment (SASE), Manali is involved in snow and avalanche studies. For avalanche prediction, snow and meteorological parameters are categorized in three groups[2]. The higher the class the less relevance are the data for avalanche. Class I data deal with snow stability information and are the most relevant data. Class II data deal with snow-pit profile which has secondary relevance, whereas Class III data are snow and met parameters and bear indirect relevance to avalanche formation. The techniques of artificial intelligence like neural networks[3,4] and expert system[5,6] can be used in addition to statistical techniques for better avalanche prediction. The present work is a step forward to develop a rule-based avalanche forecasting system using fuzzy logic. This work focuses towards extracting rules for direct action avalanches from the historic data of Stage II (Jammu and Kashmir; J&K) observatory and implementing these in expert shells.

The study area of the present work is the Chowkibal–Tangdhar (CT) axis which is the only road connecting the district of Tithwal with Kupwara, J&K (Figure 1); it falls in the Lower Himalayan Zone[7]. It negotiates and crosses the Pir Panjal range at Nastachun pass. A stretch of 36.18 km is characterized by twenty-six registered avalanche sites. This work gains importance on account of heavy pedestrian traffic (approx. 3000 personnel per month) and their unavoidable interaction with avalanches.

This communication describes the classification of variables in different fuzzy sets and rule extraction for those sets from the dataset to represent the rules in the expert shell[8–10]. It further discusses the implementation and validation of these rules, performance of the system and possible future improvements in the model.

Human thinking and reasoning frequently involve fuzzy information originating from inherently inexact human concepts and matching of similar rather than identical experiences. In classical logic, truth-values of any information are either 0 or 1, which falls under true/false duality. In fuzzy logic truth is a matter of degree; thus true value ranges between 0 and 1 in a continuous manner. The concept of partial truth characterized by fuzziness has launched the new theory of fuzzy sets, which yield a more accurate mathematical representation of perception of truth than that of crisp sets. Fuzziness occurs when the boundary of a piece of information is not clear-cut. The representation of such information is based on the concept of fuzzy set theory[11–14]. Unlike classical set theory, membership of an element to a set can be partial in fuzzy set theory, i.e. an element belongs to a set with a certain grade of membership. More formally, a fuzzy set A in a universe of discourse U is characterized by a membership function μ_A defined as:

$$\mu_A : U \rightarrow [0,1]$$

that associates with each element x of U, a number $\mu_A(x)$ in the interval [0,1], which represents the grade of membership of x in the fuzzy set A[13,15].

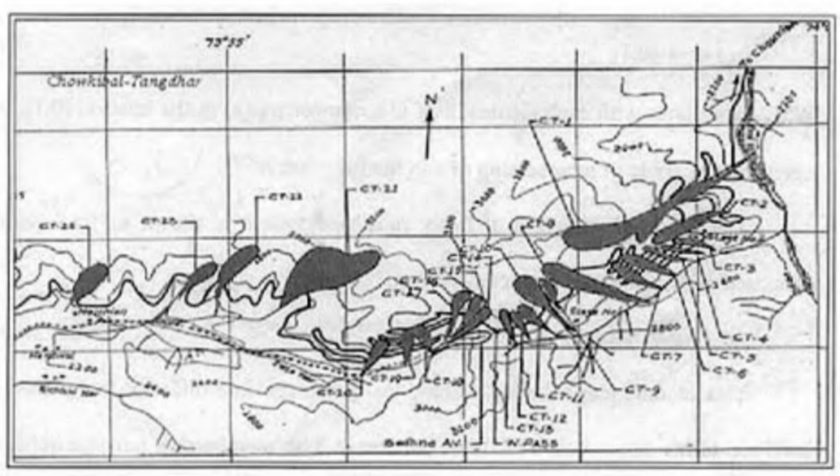

Figure 1. Avalanche sites of Chowkibal–Tangdhar axis.

The schematic diagram of fuzzy rule-based system is shown in Figure 2, which is composed of four components: fuzzification module, fuzzy rule base, fuzzy inference engine and defuzzification.

The fuzzification module maps the input numerical parameter into different fuzzy sets of the linguistic terms associated with that parameter. The membership function defined for each fuzzy set is applied on the input parameter to determine the degree of truth and rule premise.

In fuzzy rule base, knowledge acquisition is the main concern of the building of the expert system. Knowledge in the form of1 IF–THEN rules can be provided by experts or can be extracted from data. Each rule has an antecedent part and a consequent part. The antecedent part is the collection of conditions connected by AND, OR, NOT logic operators and the consequent part represents its action.

In fuzzy inference engine, the truth-value for the premise of each rule is computed and applied to the conclusion part of each rule. This results in one fuzzy subset being assigned to each output variable for each rule. For composite rules usually Min–Max inference technique is used.

Defuzzification is used to convert the fuzzy output sets to a crisp value. The widely used methods for defuzzification are centre of gravity and mean of maxima.

A direct-action avalanche is mainly due to the snow loading of the slopes during a storm. For the present study six relevant snow parameters[16] were considered for analysis from November to April of eight winters (1991–92 to 1997–98), recorded at 0830 and 1730 h daily. These are directly observed and derived variables, viz. fresh snowfall, 24-h fresh snowfall, 72-h fresh snowfall, snowfall

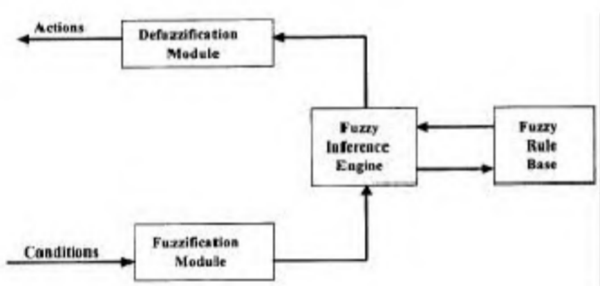

Figure 2. General scheme of a fuzzy system.

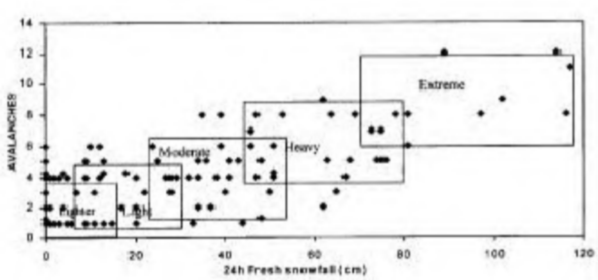

Figure 3. Distribution of 24 h fresh snowfall with avalanche activity.

Table 1. Classification criteria of avalanche danger on the study area

Avalanche danger	Frequency of avalanching
Low	Less than 3 avalanche activities in the axis
Medium	Between 3 and 7 avalanche activities in the axis
High	Between 8 and 12 avalanche activities in the axis
All round	More than 12 avalanche activities in the axis

Table 2. Nomenclature of terms used in the rule base

Terms	Description
HN	Fresh snowfall (cm)
HNF	24 h fresh snowfall (cm)
HNS	72 h fresh snow (cm)
SI	Snowfall intensity (cm)
HS	Standing snow (cm)
PS	Free penetration (cm)
CONTRIBUTION	Contribution towards avalanche activity

intensity, standing snow and free penetration. The data are segregated for avalanche and non-avalanche activity and avalanche day data are classified for different avalanche danger levels on the basis of avalanche frequency on the CT axis on that day. Table 1 describes the criteria adopted for the classification of avalanche danger into four fuzzy sets, viz. low, medium, high and all round.

The distribution of each parameter against avalanche activity was studied to extract the fuzzy sets associated with that parameter. This association allows the formulation of rules based on the influence of each fuzzy set of the parameter considered for the study with avalanche danger. Figure 3 depicts one example for the classification of 24-h fresh snowfall with avalanche activity, which gives an idea to formulate the fuzzy sets associated with it using appropriate linguistic terms. Triangular membership functions are used for defining the fuzzy sets. Figure 4 shows the fuzzy sets associated with each parameter.

The main elements of the rule-based system are database, a set of rules and an inference system[9,11,15]. The rules are operated on the database. Each rule has an antecedent condition that is either satisfied or not by the database. If the antecedent part is satisfied, the rule is fired. The inference system chooses the fired rules to compute the aggregate output of those rules.

Using fuzzy sets associated with each parameter, general IF–THEN rules are developed for each danger label of the avalanche. It is assumed that rules designed for avalanche activity ideally do not fire for non-avalanche situations. The following examples show two rules for low danger (refer to Table 2 for nomenclature of each parameter).

Rule # 1:

IF [HN] IS <HEAVY> AND [HNF] IS <MODERATE> AND [HNS] IS <LIGHT> AND [SI] IS <HIGH> AND [HS] IS <SCATTERED> AND [PS] IS <MODERATE> THEN [CONTRIBUTION] IS <LOW_DANGER>

Rule # 4:

IF [HN] IS <LIGHT> AND [HNF] IS <LIGHT> AND [HNS] IS <LIGHT> AND [SI] IS <LIGHT> AND [HS] IS <MEDIUM> AND [PS] IS <LESS> THEN [CONTRIBUTION] IS <LOW_DANGER>

In Rule # 1 contributions of fresh snowfall, snowfall intensity and free penetration are more towards low danger, as these are classified as heavy, high and moderate respectively, while the standing snow has less contribution as it is scattered. Whereas for Rule # 4 the fresh snowfall, snowfall intensity and free penetration has less contribution because these are classified as light, light and less respectively, while the contribution of standing snow is more as it is medium. In this way every parameter is analysed for the development of the rule base. A total of 101 rules were framed and fine-pruned for different danger labels during the testing of the rule base.

For any situation, more than one rule may fire and give its individual contribution towards avalanche danger; the outcome of the fuzzy inference process is a fuzzy set of a conclusion. The inference process uses Min–Max technique to assess the final situation by taking care of all global

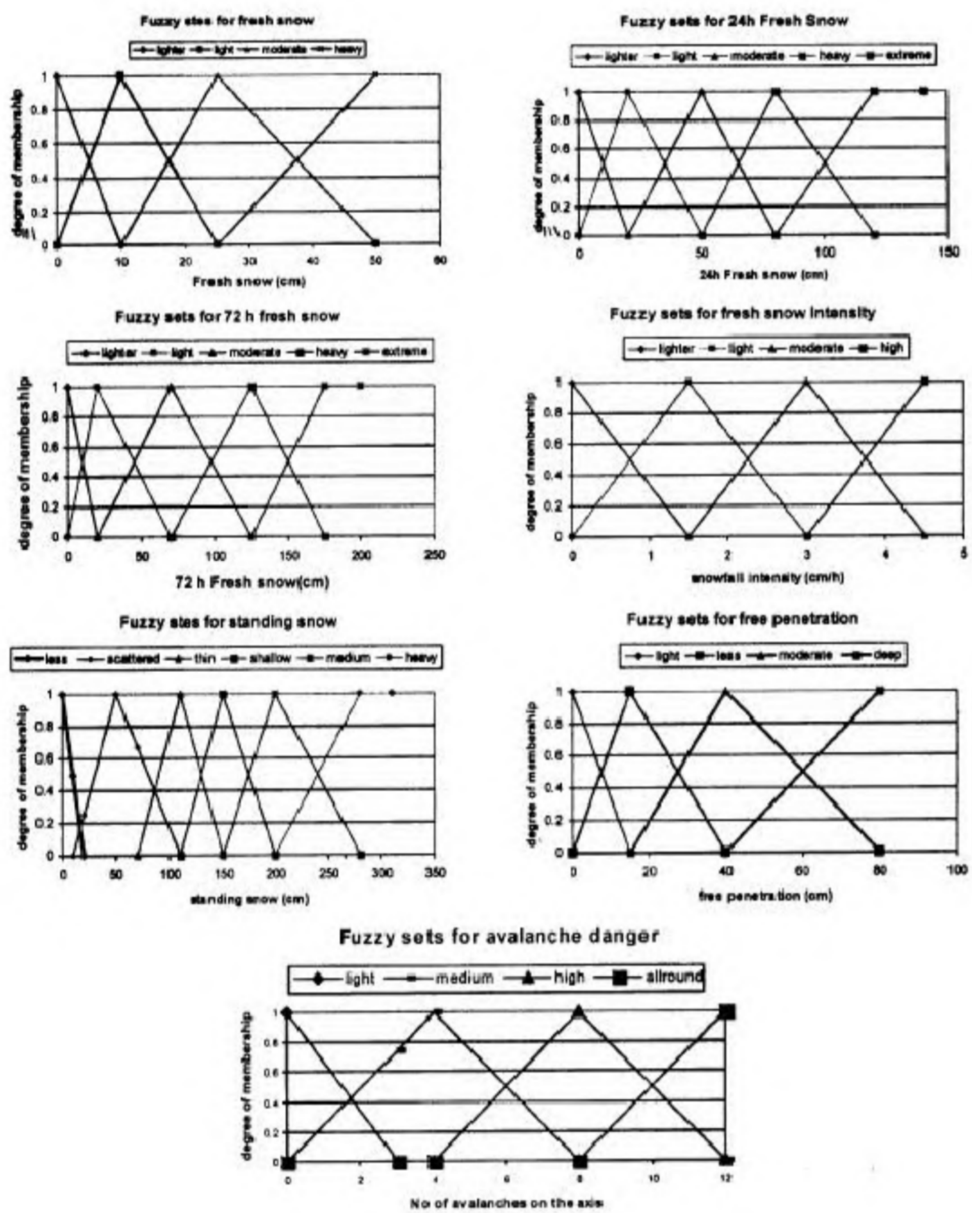

Figure 4. Fuzzy sets for input and output parameters.

contributions. For getting the appropriate crisp output, centre of gravity defuzzification technique is used. The centre of gravity is calculated by

$$x = \frac{\int \mu(x) x \mathrm{d}x}{\int \mu(x) \mathrm{d}x},$$

where $\mu(x)$ is the output fuzzy set after the implication of the rule and x is the centroid value of the fuzzy set.

One hundred and one manually designed rules were implemented and tested using FULSOME expert shell, developed by Department of Information Science, University of Otago. The implemented rules were subjected to validation. These rules were modified, fine-tuned and pruned by re-defining the rules or by modifying the fuzzy sets and finally validated for running the rule base.

A total of 137 samples of test dataset, 50 for avalanche days and 87 for non-avalanche days were run on the rule-based system. these samples were randomly selected from the entire database of the Stage-II observatory.

Figure 5 gives a comparison between the observed and model-predicated avalanche activities. Table 3 summarizes the results of the rule-based system for avalanche days. The results show that the rule-based system could predict with a reasonable accuracy of 61% for low danger cases, 58% for medium danger cases, 80% for high danger cases and 100% for all-round danger cases. Some days were without prediction: 28% for low danger cases, 17% for medium danger and 20% for high danger cases. This attributes to limitations in the decision making process due to incorrect assessment of rules. Further pruning of the rule base is needed for more accurate classification.

Table 3. Results of rule base for direct action avalanches

		Low danger case = 18		
Low	Medium	High	All round	No prediction
11	2	–	–	5
		Medium danger case = 24		
Low	Medium	High	All round	No prediction
4	14	2	–	4
		High danger case = 5		
Low	Medium	High	All round	No prediction
–	–	4	–	1
		All round danger case = 3		
Low	Medium	High	All round	No prediction
–	–	–	3	–

Table 4. Results of rule base for non-avalanche days

		Non-avalanche days – 87		
No prediction	Low	Medium	High	All round
67	15	5	–	–

A considerable number of cases were mis-classified; 11% cases of low danger were classified as medium danger cases, 17% cases of medium danger were classified as low danger cases and 8% as high danger cases. For high and all round cases, there is no such mis-classification observed. A reexamination and fine-tuning of rules required to yield better results.

Figure 6 depicts the comparison between the observed and model-accessed non-avalanche activities. Table 4 shows that for 77% cases there is no prediction because for such cases, no rule is fired and it is assumed a correct prediction for non-avalanche days. But 17% cases are classified as low danger and 6% cases are classified as medium danger. It is found that when non-avalanche days are predicted as avalanche days, some of the rules for avalanche danger were fired due to the situation prevailing for avalanche activity during that time. For such cases it is found that most of the avalanches either triggered during the period or the situation is likely for an avalanche activity in the future.

Figure 7 shows the distribution of avalanche activity when a non-avalanche day is predicted with avalanche danger. In 27% cases, avalanche activity was observed on the same day between the last observation and the current observation. In 17% cases avalanche activity was observed one day before with respect to current observation and the situation was still critical for avalanche activity. Only 6% cases were obtained when avalanche activity was observed two days before the current situation. Eleven per cent avalanche activities were observed the day after

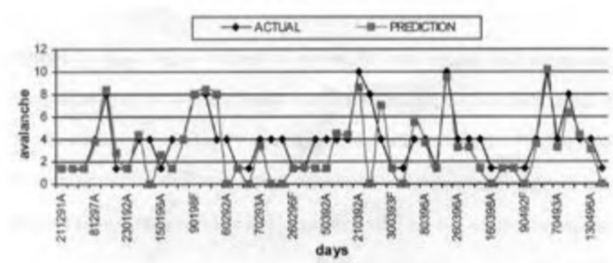

Figure 5. Comparison between actual and predicted avalanche activity.

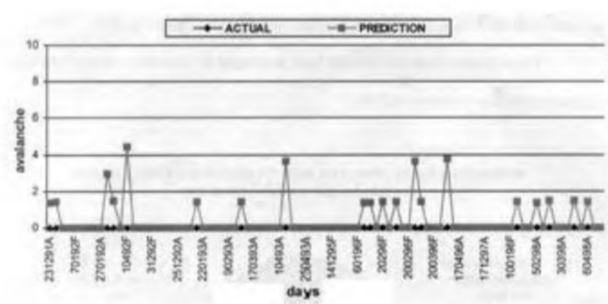

Figure 6. Comparison between actual and predicted non-avalanche activity.

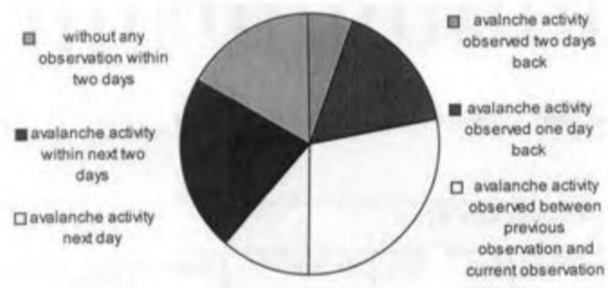

Figure 7. Distribution of avalanche activity observed when a non-avalanche day is predicted with avalanche danger.

the current prediction and 22% avalanche activities were observed in next two days after the current prediction, irrespective of other factors. In 17% cases no avalanche was observed within two days from the prediction.

These results show that the rule base developed for avalanche danger is also applicable to non-avalanche activity.

Using artificial intelligence techniques with numerical techniques can provide better results for avalanche prediction. This work is an attempt to use fuzzy logic for predicting avalanches with various danger labels. The work is focused on rule extraction for the direct action avalanches of the CT axis in J&K, for which six snow parameters are considered. A total of 101 rules were framed using the fuzzy logic theory, which analyse the data and asserts the danger label of direct action avalanches.

The result shows reasonably accurate classification for avalanche danger and also prediction of non-avalanche cases; but fine-tuning of the rule base is needed for better classification of the non-avalanche days and avalanche danger. Further investigations are required for using other parameters to predict all types of avalanches other than direct action avalanches. An in-depth data analysis is required to incorporate snow-profile data, temperature and wind data for the development of a complete rule base to predict non-avalanche activity and avalanche activity with different danger labels.

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Breakdown of synthetic potassic cordierite at low *P–T* conditions

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An experimental study on the breakdown of K-cordierite into phlogopite and Mg-cordierite has been conducted at 100–150 MPa and in the temperature range of 650–900°C under hydrothermal conditions. Potassic cordierite served as starting material and was prepared by sintering the co-precipitated gel of composition $K_{0.2}Mg_2Al_{4.2}Si_{4.8}O_{18}$ at 1200°C. All the experimental runs were carried out using Tuttle–Roy hydrothermal reactor vessels. The formation of phlogopite along with Mg-cordierite started at 700°C. This phlogopite with Mg-cordierite persisted up to 825°C and the phlogopite proportion considerably reduces beyond 825°C. At 850°C, Mg-cordierite was the only prominent phase with minor

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