WRITING A MEDIUM RANGE WEATHER FORECAST, SCIENCE OR DIVINATION

P. Eckert
Centre Météorologique
Geneva, Switzerland

Summary: some of the difficulties of issuing a medium range weather forecast are presented. We ask the question if the ensemble forecasting system is able to help the forecaster. A technique for representing the ensemble outputs with the help of a neural network is proposed.

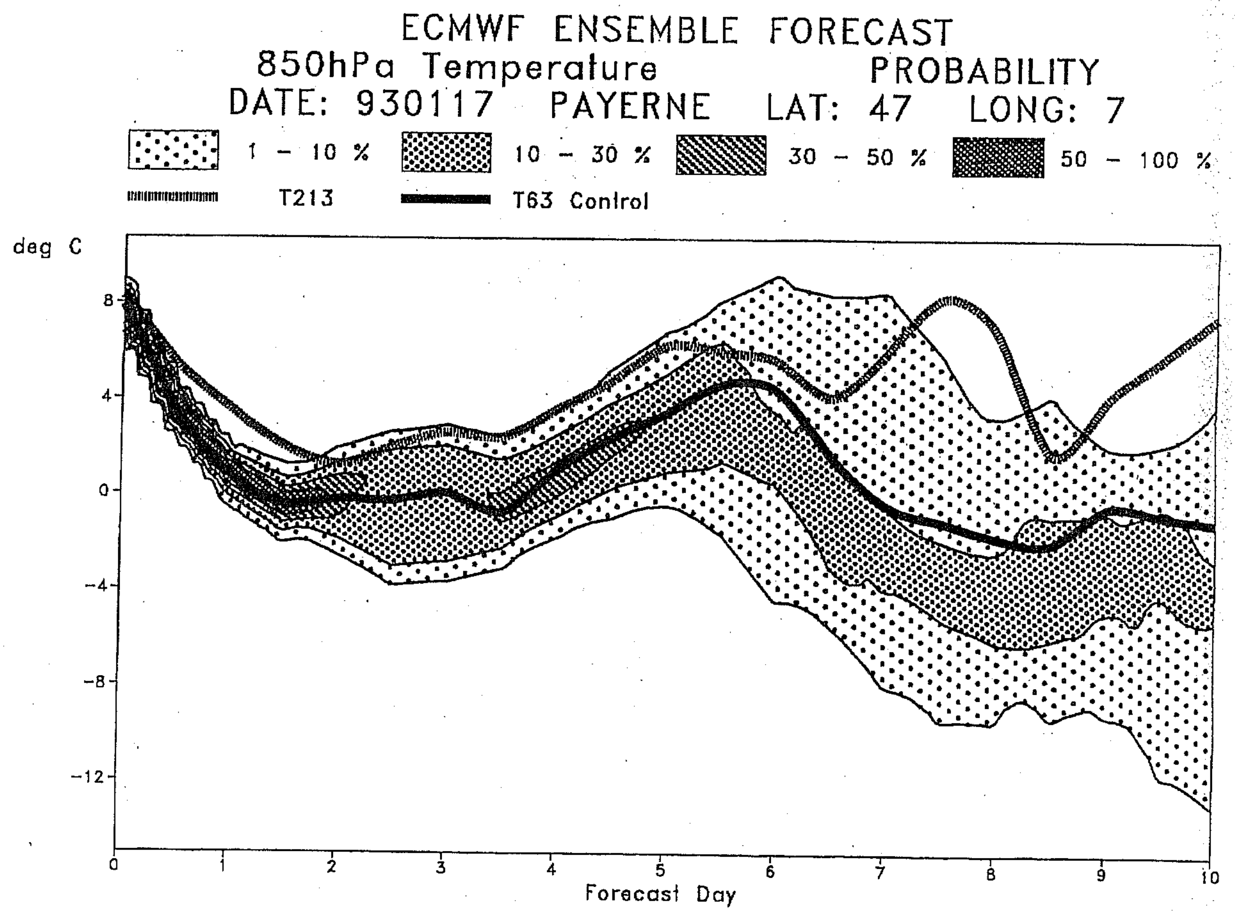
1. INTRODUCTION

Although it sometimes happens that a short range weather bulletin is written using probabilistic terms, this practice is more common in the medium range. The forecaster merely tries to share his/her lack of confidence in numerical models with the audience. This happens most of the time because different models disagree, or because the same model is incoherent with its previous run. In some cases it can happen that the forecaster simply thinks that the proposed model solution is unrealistic, but it usually needs an iron will (or a good deal of unconsciousness) to contradict the computer.

Until recently, a meteorological centre had 4 ± 2 medium range numerical models at its disposal. With the introduction of the Ensemble Prediction Scheme (EPS), ECMWF added 33 new possibilities and at the same time even more trouble in the overloaded brain of the forecaster, even though the latter is looking since a long time for a (more) objective way to assess predictability. Thus, it is necessary to strongly organize the outputs of EPS and to recognize which information can be extracted from these outputs. Is EPS really driving us to make better forecasts or is it just a safer way to tell that a forecast is uncertain?

2. EXAMPLES OF EPS OUTPUT

As all member states, we receive EPS plumes since December 1992. Unfortunately, points close to the alpine region are difficult to use, because the T63 and T213 orographies are very different there, so that usually, at low levels, the operational model rapidly exits the higher probability zones of EPS (fig. 1). A solution would be to look at more remote points (over France, Italy or Germany) or, even better, to look at a spatial repartition (of temperature anomaly probabilities for example).



SWITZERLAND

fig. 1

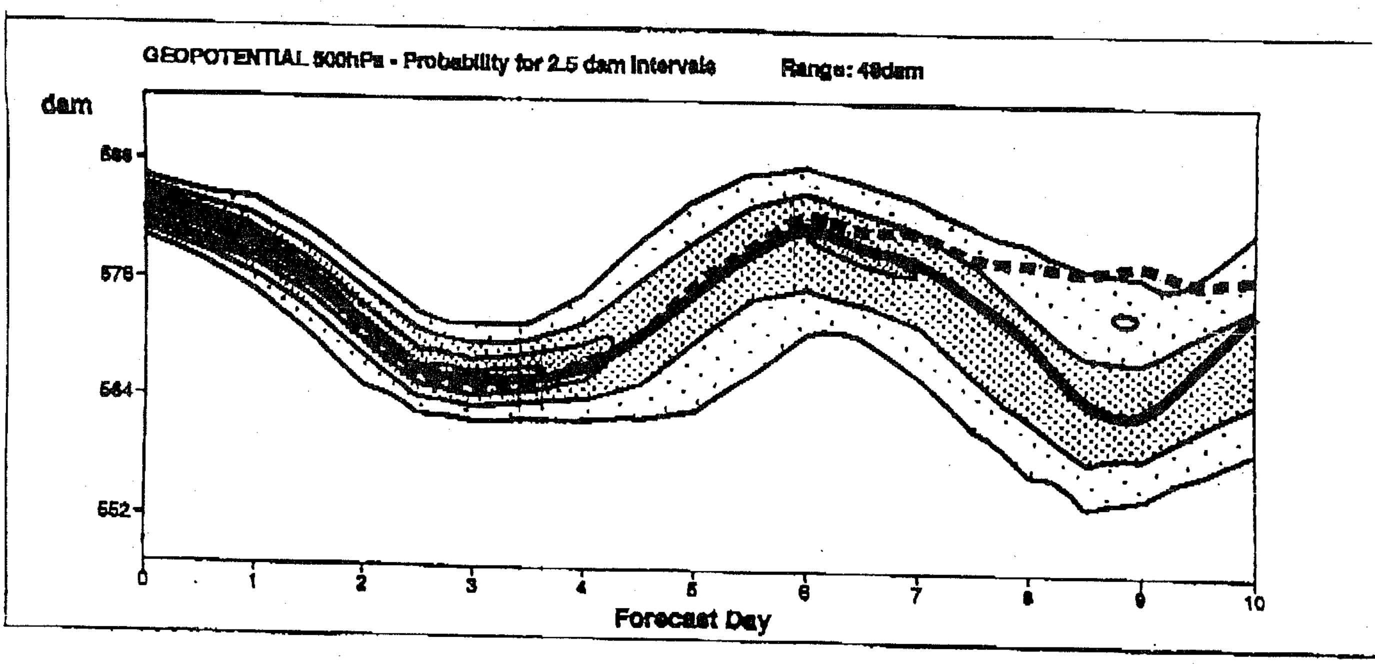


fig. 2

The same can happen for the 500 hPa heights, but not because of the orographic effect (at least not directly), but because the behaviour of both models is different. One has no difficulty if the spread of the plume is large, but what can you say when the spread is small, and the T213 is very different from the ensemble average (after day 7 in fig. 2)? Are you going to believe the sophisticated high resolution model or a bundle of "poor" resolution models? Or are you going to use T213 for making the forecast and EPS to tell you the probability that this forecast is true? In my sense, the question remains open.

What also is important to the forecaster is to acquire confidence in a forecasting system, and to achieve this, nothing is better than verification. I has been said that small spread in the plumes indicates good predictability and that large spread indicates mainly nothing. But the confidence in the system is spoiled by sporadic counter examples (fig. 3, small spread, poor verification after day 5).

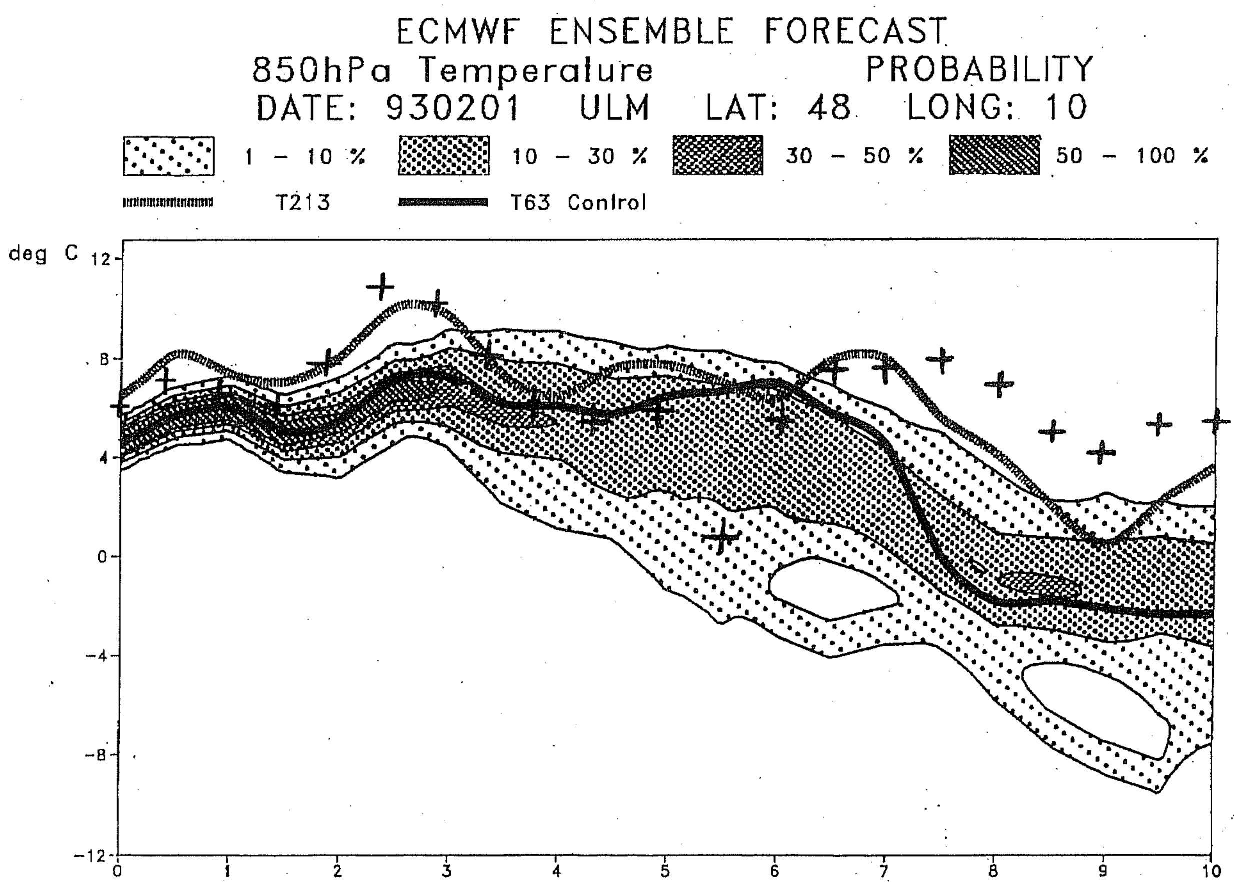


Fig. 3: crosses mark verified temperatures

A further problem is that the 500 hPa height at one point is far from being sufficient to characterize a meteorological situation. With the same height, the flow can come from any direction and have (almost) any cyclonality. This is illustrated in fig. 4, where the height is pretty constant, but the rainfall varies from day to day and from one member of the ensemble to the other. Nevertheless, EPS is sometimes very successful. On the 16th August 1993, it coherently predicted the end of our two week long summer at day 5.5 (fig. 5).

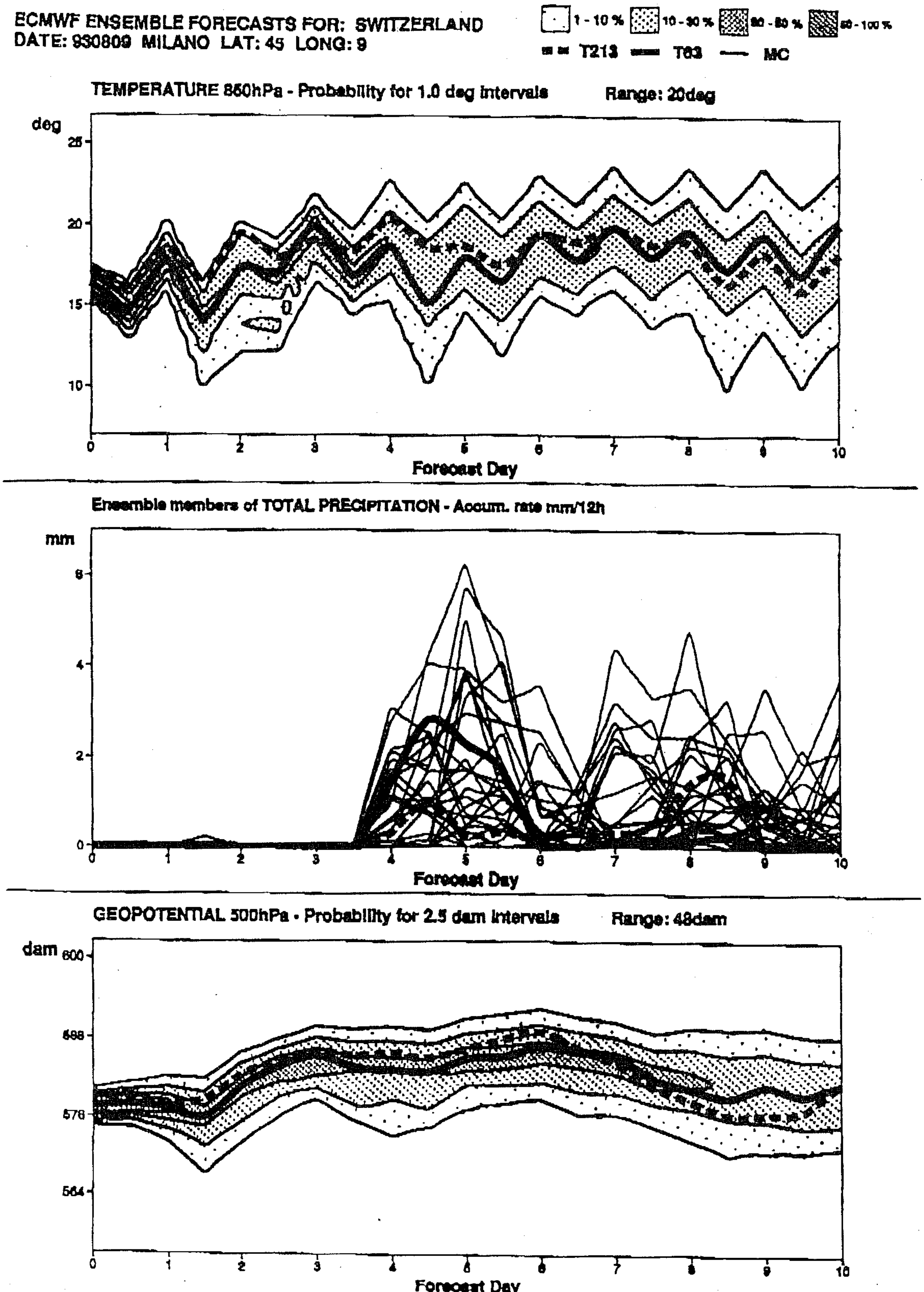

ECMWF ENSEMBLE FORECASTS FOR: SWITZERLAND
DATE: 930809 MILANO LAT: 45 LONG: 9
T213
T63
MC
TEMPERATURE 850hPa - Probability for 1.0 deg intervals
Range: 20deg
deg
Forecast Day
Ensemble members of TOTAL PRECIPITATION - Accum. rate mm/12h
mm
Forecast Day
GEOPOTENTIAL 500hPa - Probability for 2.5 dam intervals
Range: 48dam
dam
Forecast Day

Fig. 4

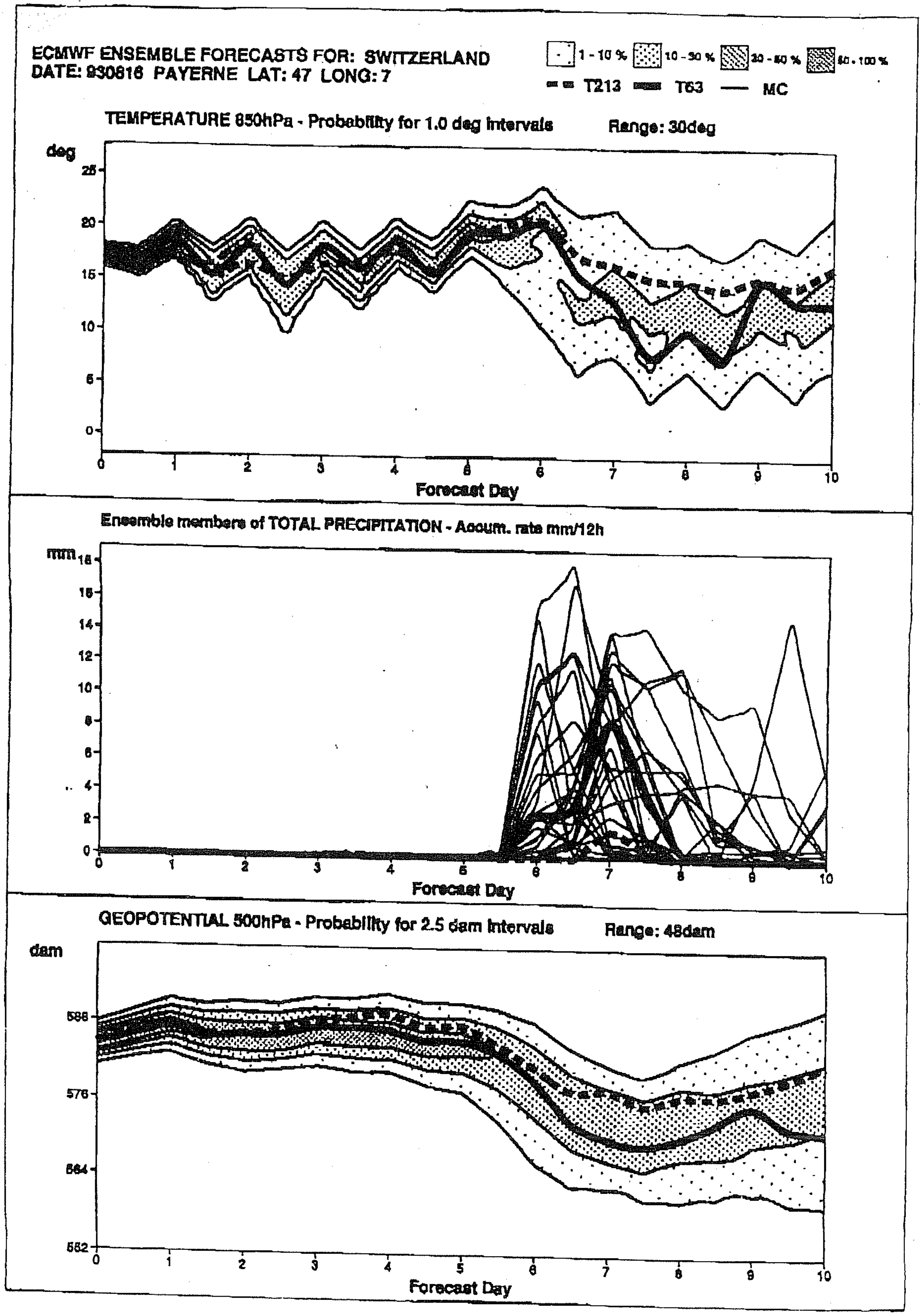

ECMWF ENSEMBLE FORECASTS FOR: SWITZERLAND
DATE: 930816 PAYERNE LAT: 47 LONG: 7
1 - 10 %
10 - 30 %
30 - 60 %
60 - 100 %
T213
T63
MC
TEMPERATURE 850hPa - Probability for 1.0 deg intervals
Range: 30deg
deg
Forecast Day
Ensemble members of TOTAL PRECIPITATION - Accum. rate mm/12h
mm
Forecast Day
GEOPOTENTIAL 500hPa - Probability for 2.5 dam intervals
Range: 48dam
dam
Forecast Day

Fig. 5

Finally, I believe that the most promising feature of EPS is to forecast different structures, alternative evolutions. It is then the task of the forecaster to choose a good option based on his experience with the model or his climatological knowledge. From this point of view, I think that, in the past, the upgrade to higher resolutions than T63 was able to improve significantly the prediction of cyclogenesis and position of lows in the Mediterranean. Thus, I have difficulties to admit that any of the ensemble members can give a realistic evolution over the latter region. My suggestion is that a future implementation of EPS should use a higher resolution than T63, at least T106.

3. PATTERN RECOGNITION BY A NEURAL NETWORK

As has already been noticed, EPS is most promising in proposing various flow patterns, but looking at 34 charts for each time step is most laborious. A way to classify properly these patterns must be found. The limitations of the actual ECMWF clustering have already been mentioned at the July 1993 expert meeting and by other contributors to this workshop. At our centre in Geneva, we were then lead to try to recognize patterns with the help of a neural network. We considered a netwok of 8x8 neurones, a so called Kohonen chart. Each neurone is stimulated by all values of a meteorological field. In our case it is a 10 by 10 grid of 500 hPa heights covering an "extended Switzerland" (cf. fig. 6). Each neurone is also connected to all others by a function which usually decreases with the distance. The way a neurone is affected by a stimulus and how it interacts with the others is given by well defined mathematical functions that will not be described here.

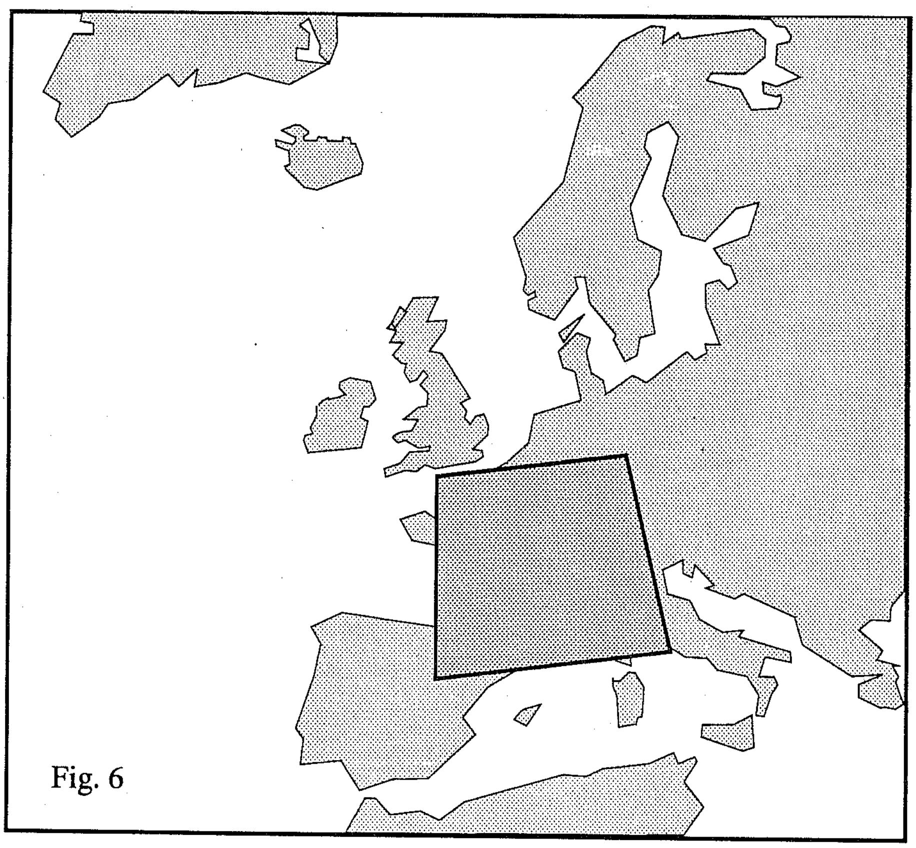


Fig. 6

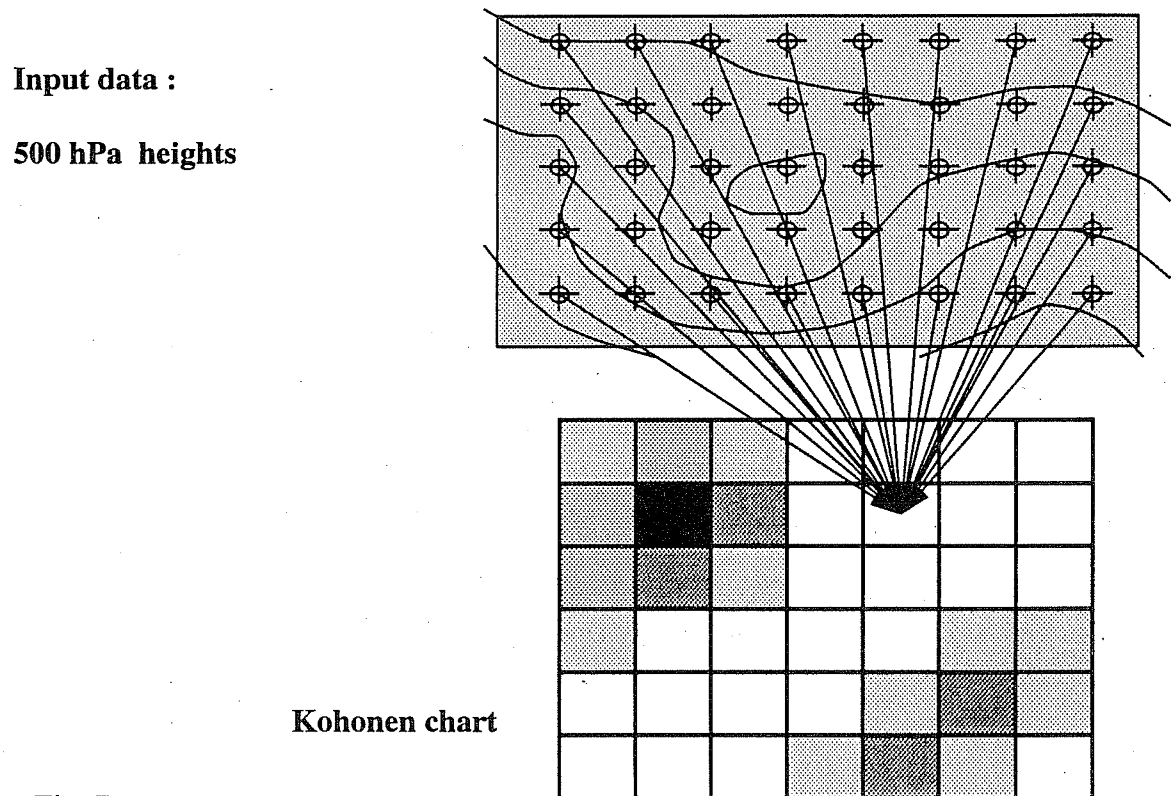


Fig. 7

The network first undergoes a process of learning in which a long set of patterns (in our case two years of EC-MWF 500 hPa height analyses) is presented sequentially, but in an order avoiding autocorelations. At the end of this learning process each neurone is sensitive to a specific pattern (meteorological situation). It can be noticed that close neurones are sensitive to analogous patterns. The set of situations connected to all 64 neurones is displayed in fig. 8.

One then can show all members of an EPS run to the network and make a graphical representation of the number of hitted neurones (fig. 9). It is then immediately visible if all forecasts are grouped in one region, two regions or more. Alternatively, for one given ensemble member, it is possible to represent a trajectory in the neurone (pattern) space. For the moment, we are not too much satisfied with the results of this classification mainly because the transition between different patterns is too smooth. This originates from the fact that we used an euclidian distance in the physical space. We believe that the use of a Mahalanobis distance will provide us a sharper pattern differencing. This work is still under progress and will certainly be presented at an other occasion.

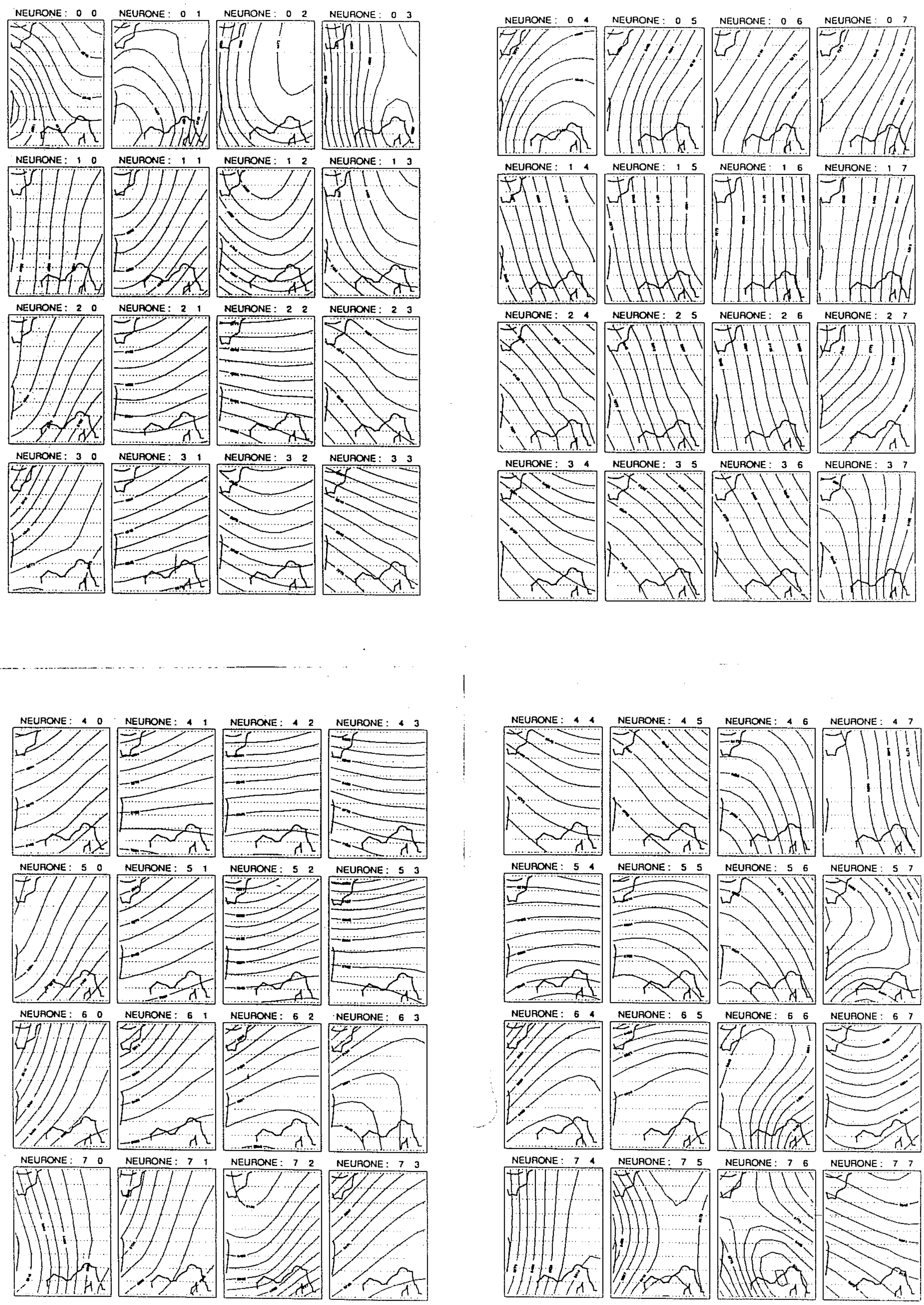

NEURONE : 0 0
NEURONE : 0 1
NEURONE : 0 2
NEURONE : 0 3
NEURONE : 1 0
NEURONE : 1 1
NEURONE : 1 2
NEURONE : 1 3
NEURONE : 2 0
NEURONE : 2 1
NEURONE : 2 2
NEURONE : 2 3
NEURONE : 3 0
NEURONE : 3 1
NEURONE : 3 2
NEURONE : 3 3
NEURONE : 0 4
NEURONE : 0 5
NEURONE : 0 6
NEURONE : 0 7
NEURONE : 1 4
NEURONE : 1 5
NEURONE : 1 6
NEURONE : 1 7
NEURONE : 2 4
NEURONE : 2 5
NEURONE : 2 6
NEURONE : 2 7
NEURONE : 3 4
NEURONE : 3 5
NEURONE : 3 6
NEURONE : 3 7
NEURONE : 4 0
NEURONE : 4 1
NEURONE : 4 2
NEURONE : 4 3
NEURONE : 5 0
NEURONE : 5 1
NEURONE : 5 2
NEURONE : 5 3
NEURONE : 6 0
NEURONE : 6 1
NEURONE : 6 2
NEURONE : 6 3
NEURONE : 7 0
NEURONE : 7 1
NEURONE : 7 2
NEURONE : 7 3
NEURONE : 4 4
NEURONE : 4 5
NEURONE : 4 6
NEURONE : 4 7
NEURONE : 5 4
NEURONE : 5 5
NEURONE : 5 6
NEURONE : 5 7
NEURONE : 6 4
NEURONE : 6 5
NEURONE : 6 6
NEURONE : 6 7
NEURONE : 7 4
NEURONE : 7 5
NEURONE : 7 6
NEURONE : 7 7

Fig. 8

Schweizerische Meteorologische Anstalt
Institut suisse de météorologie
Istituto svizzero di meteorologia

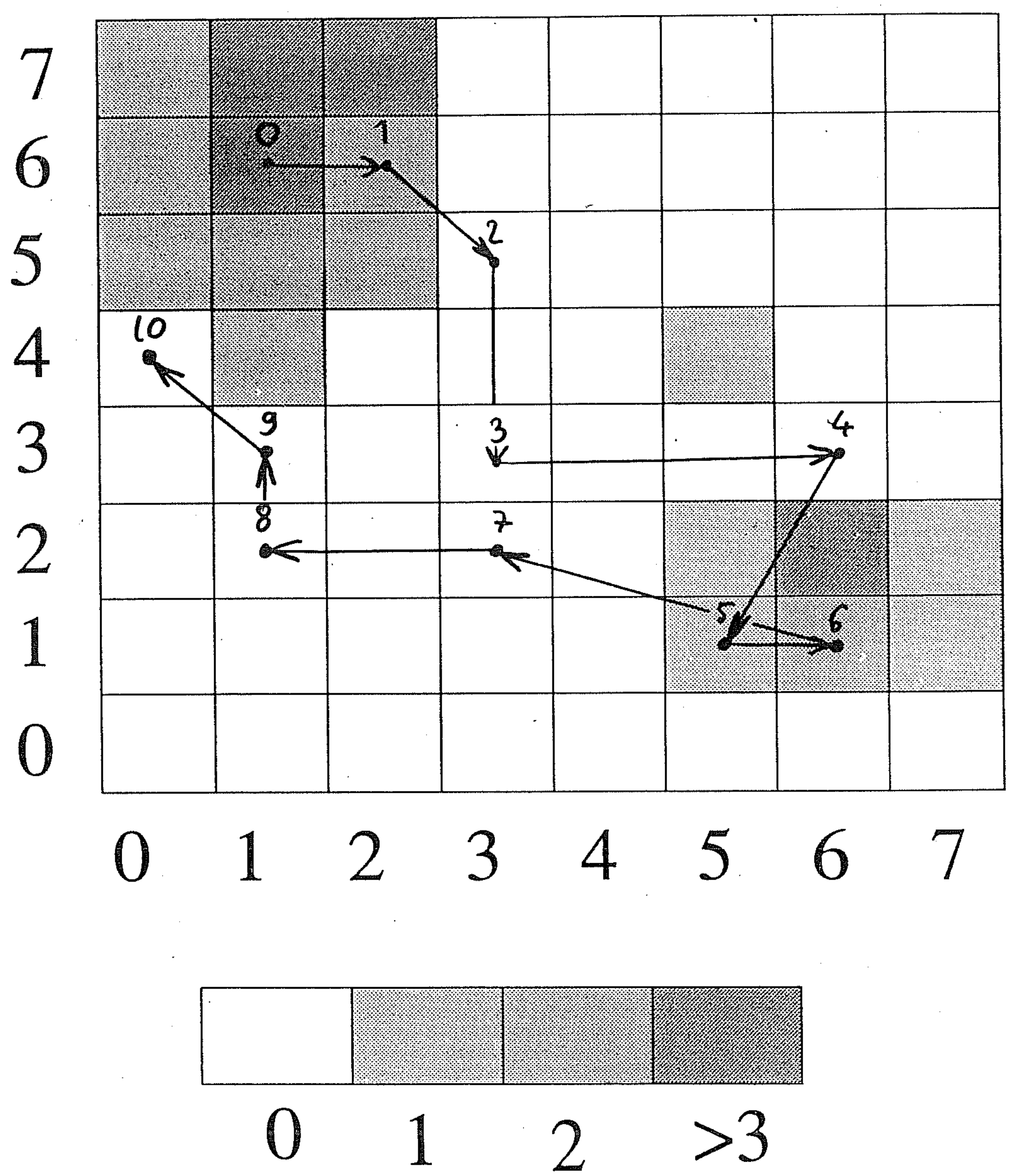


Fig. 9