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On the efficient use of satellite data to improve volcanic ash dispersion modelling

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Abstract: Volcanic ash poses a hazard to aviation, with ubiquitous jet powered aircraft being particularly vulnerable to its effects. Consequently, information about the location of ash and its predicted dispersion pattern is crucial to aviation stakeholders during eruption events. The Australian Bureau of Meteorology performs this function over a region that includes Australia, Indonesia, Papua New Guinea, and the southern Philippines. In current practice, information about the location of ash is obtained mainly from satellite imagery. Apart from the difficulty of identifying ash reliably by remote sensing, other properties of the ash cloud such as its altitude are still subject to significant uncertainties even when ash is successfully detected. On the other hand, the future location of ash is predicted by the use of dispersion models. In Lagrangian versions of these models, such as that used operationally by the Bureau, model particles, representing atmospheric pollutants such as ash, are released at specified locations and transported by gridded atmospheric winds and sub-grid turbulence. Information obtained from satellite retrievals of ash, such as its altitude, is frequently used to initialize the dispersion model. However, this is not in general done in a self-consistent and efficient manner by also taking into account how the simulated and observed ash distributions compare at a given analysis time. In this paper, we demonstrate how information about the ash distribution may be optimally integrated within the dispersion model. This is done by running a suite of dispersion model simulations with different values of the altitude of the initial ash cloud in the analysis phase of the algorithm. Pattern correlations are used to compare the simulations with the observed ash cloud. The altitude values which provide the best matches between simulations and observations are then used to initialize the dispersion model in the forecast phase of the algorithm. In this paper, we use the eruption of the Puyehue-Cordon Caulle volcanic complex, located in Chile, which occurred in June 2011 as a case study. Ash from this eruption circumnavigated the globe and caused significant disruption to aviation services in the southern hemisphere mid-latitudes, including southern parts of Australia. We demonstrate that the altitude estimates obtained from the method presented in this paper are consistent with the altitude measurements obtained from lidar instruments and superior to estimates obtained from satellite imagery alone. We also demonstrate the utility of satellite derived probabilistic forecasts of ash dispersion in the presence of significant uncertainty in the ash cloud altitude, as opposed to deterministic forecasts currently in use.

Keywords: *Volcanic ash, dispersion model, data assimilation, inverse modelling*

1 INTRODUCTION

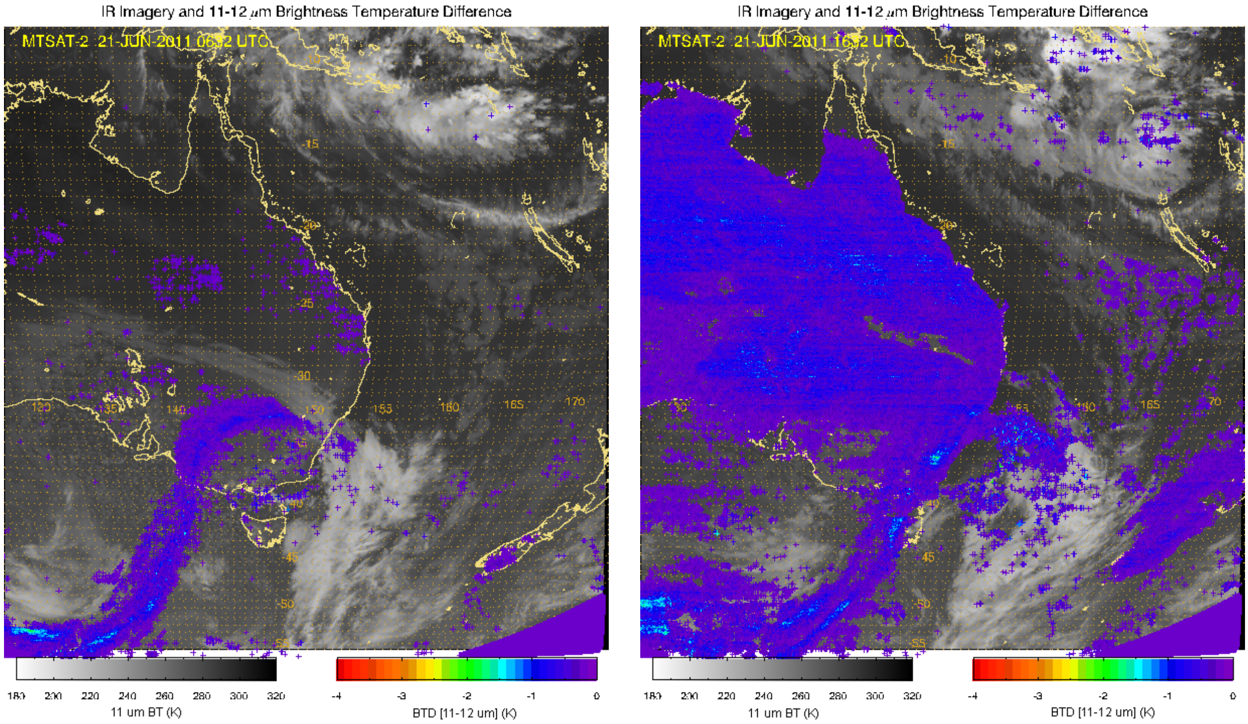
Due to the harmful effects of volcanic ash on aircraft engines, timely warnings on the current and future position of volcanic ash clouds is of crucial important to the aviation sector (Casadevall, 1994). The Australian Bureau of Meteorology provides this service over a region covering Australia, Indonesia, Papua New Guinea, and the southern Philippines. In current practice, information about the location of ash is obtained from satellite data using a variety of remote sensing techniques such as the $11-12$ micron infrared Brightness Temperature Difference (BTD) technique (Prata, 1989). Predictions of the future locations of ash are obtained from dispersion models. The Bureau of Meteorology uses the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) dispersion model (Draxler and Hess, 1998) for the purposes of providing guidance on the transport of ash. In HYSPLIT, ash particles are introduced at a source, such as the location of the volcano, and transported by gridded wind fields such those from the ACCESS suite of models (Australian Bureau of Meteorology, 2010) and subgrid turbulence. Soon after the commencement of an eruption the spatial distribution of the source is usually modelled as a line emanating from the volcanic summit to some specified maximum altitude as determined from observations. This maximum altitude is frequently estimated from the satellite derived brightness temperature (BT) but other sources of information such as pilot reports are also used. For the purposes of tracking long-lived clouds of ash it is convenient to initialise the dispersion model from satellite derived observations of ash. This is done to partly mitigate the accumulation of modelling errors over time and partly to reduce the computational time which is of crucial importance operationally. A striking example of long-lived ash in the atmosphere is the event associated with the eruption of the Puyehue-Cordon Caulle complex in Chile, starting on July 4, 2011. Ash from this eruption circumnavigated the globe at least twice and disrupted aviation services over the southern hemisphere mid latitudes for several weeks (Collini et al., 2013; Klüser et al., 2013; Vernier et al., 2013). In this study we focus on the particularly disruptive episode which occurred over south-east Australia on June 21. Conventional height estimation methods based on the MTSAT geostationary satellite do not work well in this case due to the optical thinness of the long-lived ash cloud. However, the ash dispersion pattern, being strongly dependent on the winds, contains important information about the possible altitude of the ash cloud. This information can be extracted from the ash distribution pattern by an appropriate inverse modelling technique as shown in this paper.

2 METHODOLOGY

The aim of this methodology is to tune the dispersion model to satellite observations by systematically varying the model parameters (such as the vertical extent of the ash source) and finding the parameters that best fit the observations. The resulting optimised simulation then becomes a basis for making better forecasts of ash transport. To quantify the relationship between the dispersion model output and the satellite observations, we introduce a statistical measure, namely the pattern correlation

$$r(\mathbf{p}) = \frac{\sum_{i=1}^{i=N}[x_i^m(\mathbf{p}) - \bar{x}^m(\mathbf{p})][x_i^o - \bar{x}^o]}{\sqrt{\sum_{i=1}^{i=N}[x_i^m(\mathbf{p}) - \bar{x}^m(\mathbf{p})]^2}\sqrt{\sum_{i=1}^{i=N}[x_i^o - \bar{x}^o]^2}}. \tag{1}$$

Here x_i^m and x_i^o are model and observed values (generally based on satellite retrievals) of the ash loading at a grid point i; $\bar{x}^m$ and $\bar{x}^o$ are the corresponding spatial mean values; and N is the number of grid points. The model values are dependent on the set of parameters represented by $\mathbf{p}$, and hence the pattern correlation is also dependent on $\mathbf{p}$. In this paper, we shall consider the problem of determining the altitude, h_0, of the ash cloud and hence $\mathbf{p} = h_0$ is a scalar but in general it is a vector with each component representing some unknown model parameter. With this definition $r = 1$ corresponds to perfect correlation and $r = 0$ to absence of correlation. Additionally, because ash mass loadings from the satellite retrievals are frequently difficult to estimate and subject to significant uncertainty, we first convert the satellite retrievals into binary digital form; that is, we define areas with ash to have a loading of 1 irrespective of the actual estimated loading and areas without ash to have loading of 0. The dispersion model mass loading output is defined in a similar digital form prior to calculating the pattern correlation. The model parameters are then systematically varied, by defining a parameter grid, and the pattern correlation between the resulting simulated ash loading and observed loading—both in digital form—calculated for all values of the model parameters on the parameter grid. The set of parameters $\mathbf{p_m}$ that yield the maximum pattern correlation are then formally the solution to the optimisation problem. This defines the deterministic version of the inverse model. However, we recognise that both the model and observations contain errors that may mask the correct solution. We hypothesize therefore



(a) (b)

Figure 1. Satellite detections of ash based on negative BTD (purple/blue) at (a) 0632 UTC and (b) 1632 UTC using MTSAT-2. Also shown is the 11 micron BT in grey scale.

that the solution is contained within the range of pattern correlation values defined by

$$r(\mathbf{p}) \geq \alpha r(\mathbf{p_m}) \tag{2}$$

for values of α close to unity. In this view, $\alpha = 1$ defines the deterministic inverse model, for then only the parameter set yielding the maximum value of r is selected. Conversely, when $\alpha = 0$ then all parameter values are selected and the inverse model becomes, in effect, redundant. We have found empirically that values of α of about 0.95 work quite well in being able to capture the correct solution as determined in numerous case studies while also capturing typical errors in the inversion process as shall be further demonstrated in this paper. Apart from α, this method does not require any ad hoc parameters which is to be contrasted with methods employing regularised least-squares (e.g, Eckhardt et al. (2008) and references therein). Additionally, no assumption is made on the linearity of the model response, which makes the method more general in scope. The model parameter values satisfying Equation (2) are then used in the forecast phase of the algorithm to provide probabilistic forecasts of ash bearing locations by running multiple simulations employing these values. The probability of ash at a given location is defined as the fraction of simulations yielding ash at that location in the forecast phase of the algorithm.

3 ASH REMOTE SENSING

Here we shall focus on retrievals of ash by the MTSAT-2 based Brightness Temperature Difference (BTD) algorithm (Figure 1) and the CALIPSO lidar (Figure 2) during the Cordon Caulle ash event in the vicinity of south-east Australia on June 21, 2011. The MTSAT-2 images reveal the geographical location of the ash cloud by identifying regions with negative values of BTD, which are associated with ash (Prata, 1989). False detections do occur, however, as can be noted in Figure 1(b) in particular, in which negative BTD values occur over much of the Australian continent. Operationally, the skill of the forecaster is still required to manually

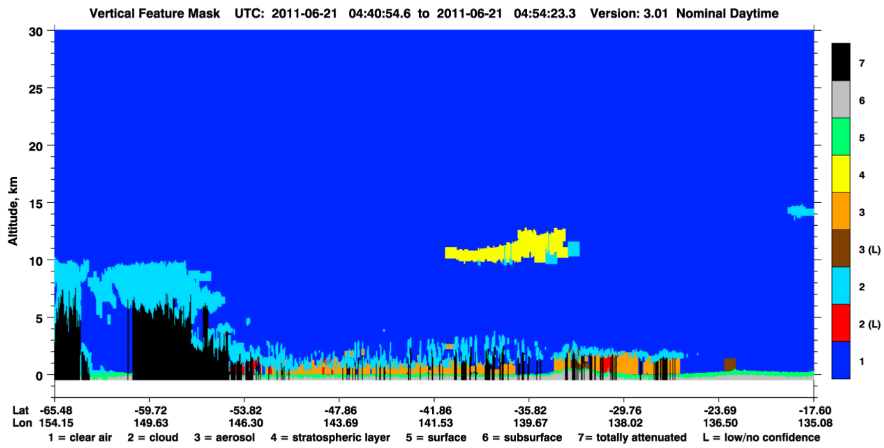


Figure 2. CALIPSO lidar image at approximately 0500 UTC. The ash-bearing locations are shown in yellow.

delineate the areas likely to contain ash from such images. We can see that at 0632 UTC the ash is over the south-eastern part of Australia and is moving to the east as can be deduced by the ash pattern at 1630 UTC for example (ignoring the false detections of ash over much of the continent). By considering several such images and by an inspection of the prevailing wind pattern, it is clear that the ash emanates from higher latitudes ($> 50°$S) and from the west. The ash seen in this image is part of a long train of ash that passed twice over the south of Australia in June 2011. The ash was also detected by CALIPSO (image downloaded from http://www-calipso.larc.nasa.gov/) at around 0500 UTC as shown in Figure 2 and this reveals the profile of the ash cloud and hence its altitude. It can be seen from this image that the ash identified by CALIPSO is at an altitude of about 11-13 km. The information about the geographical location of ash obtained from MTSAT-2 and the vertical location obtained from CALIPSO may be combined to initialise the dispersion model, from which forecasts of ash transport may be obtained. However, as CALIPSO is on board a sun-synchronous polar-orbiting satellite it is not possible to rely on it for operational purposes in general. In most cases, ash emitted into the atmosphere by volcanic eruptions is not detectable by CALIPSO simply because its orbit does not pass over the ash cloud. An alternative means of determining the altitude of the ash cloud based on a geostationary satellite such as MTSAT-2 is therefore required for operational purposes. We propose to use the inverse modelling technique described in this paper for this purpose.

4 INVERSE MODELLING RESULTS

In what follows we shall show how the inverse model may be used to obtain an estimate of the height of the initial ash distribution (at 0632 UTC), shown in Fig. 1(a), without recourse to CALIPSO data. The dispersion model is initialised by introducing particles within the model in a region defined by the ash-bearing locations in Fig. 1(a). When initialising the dispersion model from a satellite-retrieved ash distribution it is useful to manually define the boundaries of the ash cloud rather than ingest the satellite retrievals directly. The reason for this is that the satellite retrievals inevitably contain errors (in the form of missed and false detections) that will be propagated forward in time by the dispersion model and ultimately lead to misleading forecasts as discussed above. ACCESS-R meteorological model fields are used to transport the model particles. The height of the initial ash distribution is varied to find the height at which the pattern correlation between simulations and observations is a maximum. For the observations, we use satellite data—also manually delineated—at six different times between 0732-1232 UTC. This is a one-dimensional inverse model as only one variable, namely the height, is optimised.

The results obtained from this procedure are shown in in Table 1. They show that ash altitudes in the range 12-14 km are inferred by the inverse method when using observations between 0730 and 1230 UTC. This altitude range is broadly consistent with the observed ash altitude of 11-13 km demonstrated by CALIPSO (Fig. 2) thereby demonstrating the soundness of the inversion technique. Fig. 3(a) shows the variation of the pattern correlation (scaled by the maximum value) with the ash altitude at 1030 UTC. Although clearly the

Table 1. Inferred 0630 UTC ash cloud altitude h_0 as determined from observations at different times using the one-dimensional inverse model. The corresponding pattern correlations (r) are also shown.

Time (UTC)	h_0 (km)	r
0730	12	0.74
0830	12	0.77
0930	12	0.75
1030	13	0.76
1130	12	0.61
1230	14	0.61

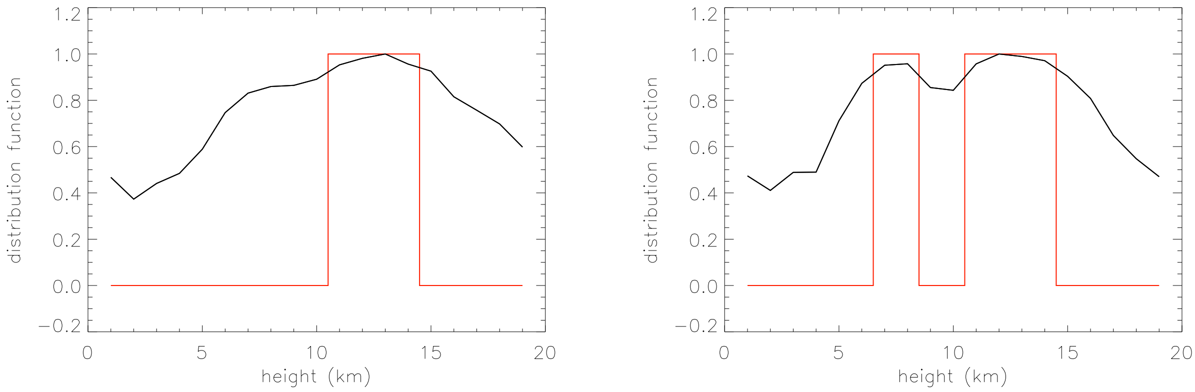
distribution is peaked at 12 km, the inversion process also includes values in the range 11-14 km (with equal probability) as part of the solution ensemble. This probabilistic distribution is shown in red. This range appears to be consistent with the variability of the maxima across different timesteps (12-14 km). Similar ranges are observed at other timesteps; for example 10-15 km at 0830 UTC, 11-13 km at 0930 UTC and 13-14 km at 1230 UTC. However, it should be noted that at some timesteps the distribution can take a bimodal character, with the distribution at 1130 UTC [Figure 3(b)] being a prime example. Such a distribution indicates the possibility of ash in the vicinity of both peaks. This could either be an artefact of the ash delineation process or an indication of ash at both levels; it is impossible to decide without additional observations.The utility of the probabilistic formulation then becomes particularly apparent, for forecasts corresponding to both peaks shall be retained (provided of course that the peaks do not differ too much in magnitude).

The ash distribution patterns at 1030 and 1130 UTC, both optimally simulated and manually delineated, are shown in Figure 4. The agreement between simulations and observations is quite good although some discrepancies can be noted. Firstly, there is a tendency for the simulated ash to extend beyond the delineated observed ash boundary over the Tasman Sea, particularly at 1130 UTC. Additionally, at 1130 UTC the simulated ash is also slightly north of the observed ash boundary. These differences could be related to errors in the dispersion model, particularly due to errors in the wind fields, or to errors in correctly delineating the ash boundaries from the satellite retrievals (i.e. observational errors). The absence of ash south of about 45°S arises because no ash was introduced south of 50°S at 0630 UTC (the start of the simulation) in the model. As noted above, a long train ash was observed to move in an eastward direction at latitudes south of 50°S and then northwards from about 140°E. New ash was therefore injected into the region of interest well after 0630 UTC which is not captured in the simulations.

Figure 5 shows the 1630 UTC forecasts of the ash probability distributions as determined from analyses (model optimisation) at 1030 and 1130 UTC. Generally these forecasts appear to be the consistent with the distribution of ash shown in Figure 1(b). There does however seem to be a tendency for the simulated ash to be moving too rapidly to the east as can be noted over the Tasmanian region in the 1030 UTC based forecast. The 1130 UTC based forecast has more spread in the ash distribution; this is consistent with its bimodal probability distribution function in parameter space (see Figure 3). A striking difference however is the appearance of a second (southward) branch over the Tasman Sea. Although this branch is associated with relatively low probability compared to the main eastward branch, it is intriguing that the satellite image in Figure 1(b) does show some evidence of ash in the region corresponding to the simulated secondary branch. It should also be noted that Vernier et al. (2013) do discuss the possibility of lower altitude ash within the region on June 21. Although evidence of this lower altitude ash is not as strong as that for high altitude ash (11-13 km), this example does illustrate the importance of probabilistic forecasts of ash and of the inverse model in identifying regions of high likelihood in parameter space.

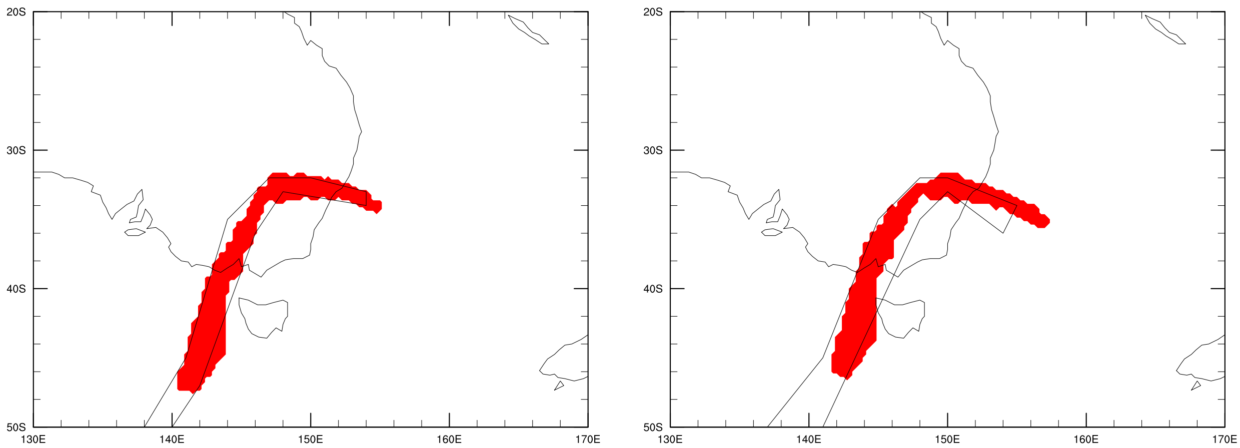
5 CONCLUSIONS

In this paper we show how an inverse modelling method may be used to infer the altitude of the ash cloud originating from the eruption of the Puyehue-Cordon Caulle volcano complex in Chile and passing over south-east Australia on June 21, 2011. The method is based on running a suite of dispersion model experiments, each with a different value of a model parameter—in this case the ash cloud altitude—and choosing the parameter values which best match the available observations—in this case MTSAT-2 satellite images employing the BTD ash retrieval algorithm. We showed that the inverse model yielded on average a value of about 12 km for the ash cloud altitude, consistent with CALIPSO lidar retrievals of ash at around that time. We also showed the utility of probabilistic forecasts of ash which can be obtained from this method in identifying all the possible future locations of ash.



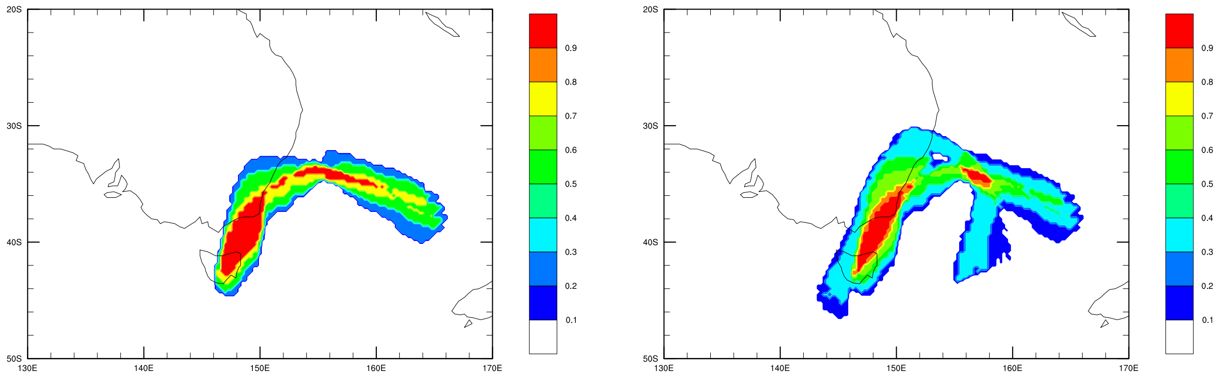
(a) (b)

Figure 3. Pattern correlation scaled by maximum value (black) and discrete unnormalised probability distribution (red) at (a) 1030 UTC and (b) 1130 UTC.



(a) (b)

Figure 4. Optimal simulations of ash distribution patterns (in red) and corresponding observed ash ash boundaries (polygons) at (a) 1030 UTC and (b) 1130 UTC.



(a) (b)

Figure 5. Forecasts of ash probability distributions at 1630 UTC based on analyses at (a) 1030 UTC and (b) 1130 UTC.

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