FORECASTING SURFACE CURRENTS MEASURED WITH HF RADAR

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ABSTRACT Utilization of real-time surface current data with oil spill models requires forecasting currents for lead times of 24 to 48 hours. A forecasting method based on tidal decomposition and an ARMA analysis of residuals has been derived and tested using the 1992 Juan de Fuca SeaSonde database of hourly surface currents. Results show that, for this particular region, most of the observed current can be accounted for by the tide and the short-term residual mean. A portion, representing about 15% of the variance, was found to be associated with the turbulent eddy field. The radar current measurements provide spatial estimates of the kinetic energy in this turbulent component, and of the associated eddy diffusivity. Thus, the current forecasting algorithm provides useful predictions of both the slowly-varying deterministic flow field, and the spatial variations of the turbulent energy and diffusivity.

1 INTRODUCTION

High-frequency radar systems, such as the SeaSonde (Hodgins et al., 1993--these proceedings), are capable of measuring spatially dense surface currents in real-time. Current maps are typically available on an hourly basis, covering 1,000 to 2,000 km^2 or more. An important issue in utilizing such real-time information with oil spill models concerns forecasting currents for lead times of 24 to 48 hours. Forecasting algorithms could be based on measurements alone, on assimilation of observations into numerical hydrodynamic models, or a combination of these two approaches. In this paper, a purely measurement-based algorithm based on tidal decomposition and an ARMA analysis of residuals has been derived and tested using the 1992 Juan de Fuca database of hourly surface currents (Hodgins et al., 1993). This approach is about the simplest that one could take to obtain an estimate of future flow conditions, incorporating the most recent history.

In most coastal areas surface currents result from a combination of tidal, buoyancy and wind-induced forces that occur over a range of frequencies from a few cycles per hour, to less than one cycle every few weeks. The tidal current component is deterministic and can be isolated in the total signal by harmonic analysis. The other components are less amenable to analysis and prediction.

The model examined here is based upon harmonic decomposition of the measured signal into its tidal and residual components, modelling each band separately to forecast 48 hours into the future, and recombining the components to give the total current. The residual component has not been further broken down into a low-

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Table 1: Extraction of Tidal Constituents for Various Record Lengths

Record Length (hours)	Record Length (days)	Period (hours)	Constituent	Magnitude (per cent M^2)
13	0.54	12.42	M^2	100
24	1.00	23.93	K^1	58.4
328	13.66	25.82	O^1	41.5
355	14.79	12.00	S^2	46.6
355	14.79	7.99	SK^3	< 10
662	27.58	22.31	OO^1	1.8
662	27.58	26.87	Q^1	8.0
662	27.58	24.83	NO^1	3.3
662	27.58	23.09	J^1	3.3
662	27.58	12.66	N^2	19.2

In practice, only those constituents of relative strength greater than 10 are of importance.

Time-series of surface current have been extracted from the SeaSonde dataset and harmonically analyzed to give the tidal portion of the signal. The tidal analysis was done for two input record lengths of 5 days and 21 days in order to examine the influence of discriminating the main diurnal and semidiurnal constitutents. As expected, the 21-day analysis provided a tidal signal accounting for more of the variance than the 5-day analysis (about 6%); however, it is clear that in this area, the tide accounts for the great majority of the signal (Fig. 2), and that a reasonable prediction can be obtained with a relatively short record.

3 EXTRAPOLATION OF THE RESIDUAL CURRENT

The residual current is defined as:

$$u_{res} = u - u_{tid}; \quad v_{res} = v - v_{tid} \tag{1}$$

dropping the time notation for clarity, and follows directly from the tidal analysis. The time-series u_{res} and v_{res} were modelled as an autoregressive process of order m, denoted AR(m). This stochastic process is a special case of the class of models known as ARMA (autoregressive moving average). In the AR(m) model, z_t, the deviation from the mean at time t, is treated as being regressed on the m previous deviations z_t, z_{t-1}, z_{t-2}, z_{t-3}, ... z_{t-m} as follows:

$$z_t = \alpha_1 z_{t-1} + \alpha_2 z_{t-2} + \ldots + \alpha_m z_{t-m} + \epsilon_t \tag{2}$$

where α_1, α_2, α_3 ... α_m are constant weights, and ϵ_t is a time-series of uncorrelated random components with zero mean (white noise). Such a model is capable of generating realistic environmental time-series. Properties of the ARMA process are described in more detail in Hodgins (1993b).

The objective is to determine the order m of the model, and to calculate the constant weights α_1, α_2, α_3 ... α_m, given the observed time-series. Equation (2) can then be

The choice of the order m of the model was influenced by the following considerations. Models of high order are capable of detecting and parameterizing many superimposed oscillations at different frequencies, just as a linear differential equation of high order has solutions made up of a superposition of many damped harmonics. However, a limit to the ability to resolve these frequencies is imposed by the length of the observed time-series, analogous to the Nyquist criterion in Fourier analysis. Jenkins and Watts (1968) suggest that the order m be determined by fitting processes of different orders, and examining the residual variance for a number of test time-series.

Tests were carried out on n hours of residual current data from the Juan de Fuca dataset to investigate the effect of increasing the order of the model on the residual variance. In general, the residual variance decreased rapidly as the order was increased from zero to one, and continued to decrease slowly as the order was increased to around n/10. The residual variance then remained relatively constant, and started to rise as the order increased beyond n/3. There is a fundamental restriction that the order m cannot exceed the record length n. As a result of these tests, it was determined that a model of order m = n/4 would be used. In addition, a ceiling of 72 was placed on m, in order to avoid inverting an excessively large matrix for long time-series. Thus, values from no more than the previous 3 days are used in (2) to generate future values. However, all previous data are used in the calculation of the coefficients $\alpha_1, \alpha_2, \alpha_3 \ldots \alpha_m$.

Equation (2) was then used to generate a 48-hour forecast for the future values of the time-series, with $\epsilon_t = 0$. Finally, the absolute residual current for each direction was calculated by adding the previously-subtracted mean μ to the forecast time-series u_{res}, v_{res}.

4 TESTS AND RESULTS

Five experiments using this algorithm were carried out on time-series data from point 1 (Fig. 1) to test the prediction method, and to examine the nature of the currents in Juan de Fuca Strait. A 9-day period, from 17:00 GMT on July 10, to 17:00 GMT on July 19, 1992, was selected for these tests. This period provided the longest input time-series of large tides followed by two days of good data against which to compare the forecast values. The last 48 hours were reserved as the prediction interval, and the analysis was carried out for:

Experiment	Input data record length (analysis period - days)	n (hours)
1	1	24
2	2	48
3	3	64
4	5	116
5	7	164

With these input data record lengths the same tidal constituents are estimated in each experiment, although with different amplitudes and phases, and the tests simulate conditions within the first few days of radar deployment during an incident response.

The ability of the ARMA model for predicting the residual current is governed to a large extent by the autocovariance properties of the signal. Estimated

The lower-order ARMA process for 3 days of input data, with these acf characteristics, yields a predicted signal that damps quickly over the first 48 hours. The higher-order ARMA processes associated with the 5- (Fig. 4) and 7-day input series yield greater variation in the predicted signal; however, the fit to the observed data is not better in any deterministic sense.

Given the nature of the observed residual flows in Juan de Fuca Strait, there is no benefit to a high-order ARMA process, and a second- or third-order process would be as justifiable as one with n/4 for an arbitrary-length input data record.

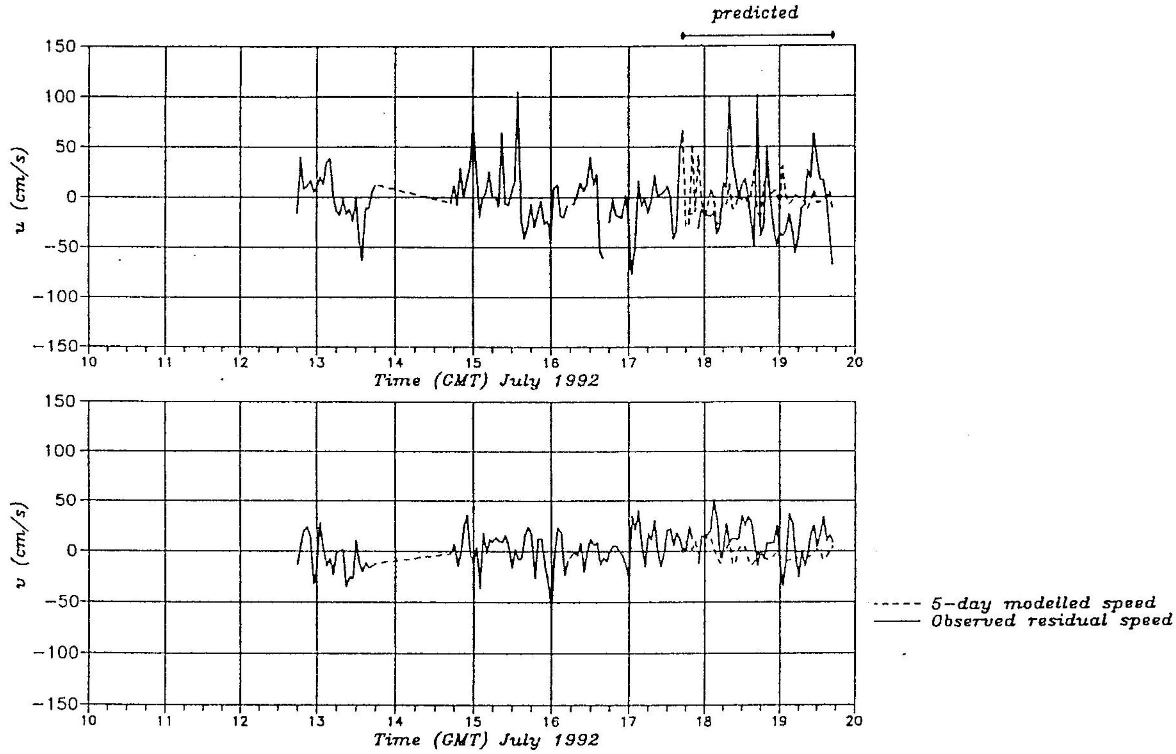


Fig. 4 Comparison of the predicted and observed residual current signals for a 5-day analysis period at point 1.

The total current prediction is given by:

$$u_{pred} = u_{tid} + u_{ARMA(m)} + \mu_u$$
$$v_{pred} = v_{tid} + v_{ARMA(m)} + \mu_v \qquad (4)$$

where $u,v_{ARMA(m)}$ are the m-th order ARMA model values, and $\mu_{u,v}$ is the mean of the residual current signal.

The five experiments discussed previously with the ARMA model were repeated, applying equation (4) for each different analysis period. The predicted u and v time-series for experiment 3 are shown in Fig. 5. Comparison of these forecasts

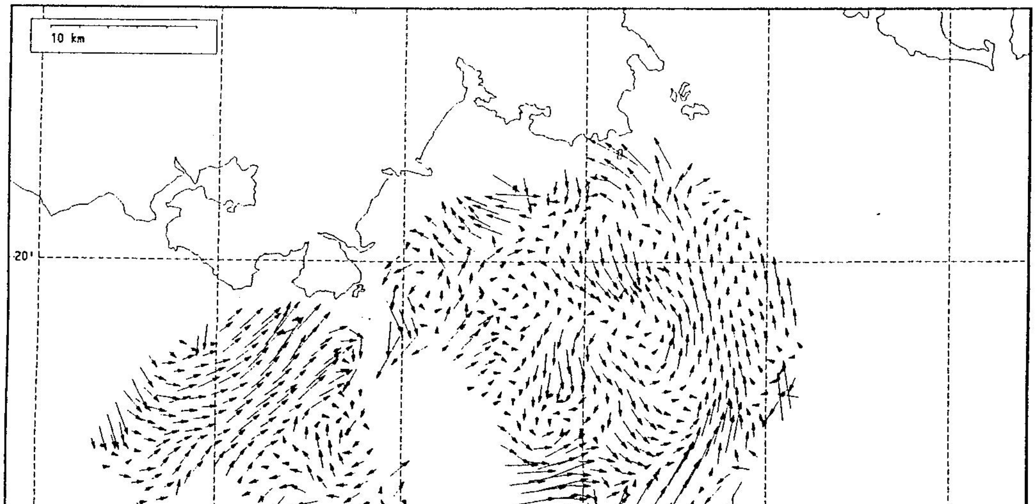
Since the residual component has a small influence, the short-term predictor is better than the 5- to 7-day predictor. Once the tidal analysis exceeds 14 days, then the fortnightly modulation becomes resolved and the accuracy improves.

Table 4.2: RMS Difference In Current Components $(u^{tot}-u^{pred})$ **and** $(v^{tot}-v^{pred})$

Experiment	u-component (cm/s)	v-component (cm/s)
1	44.97	19.10
2	39.72	20.62
3	40.67	18.70
4	48.77	21.65
5	46.18	21.59

6 CONCLUSIONS

It is apparent from the harmonic time-series analysis, and the nature of the acf of the residual currents, that there is a part of the observed flow that is unpredictable by tide and the autocorrelation structure of the non-tidal portion. Inspection of the residual current maps shows that much of the rapid variability in the residual time-series results from eddies that develop in the flow field at large scales, from fronts



Residual current field, Juan de Fuca Strait, 05:00 Z, July 19, 1992.

Fig. 6 Example of the turbulent residual flow field illustrating the spatially coherent eddy features.

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