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Mapping the Northeastern Chukchi Sea Surface Currents and Their Dynamical Response Under Different Environmental Conditions

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Motivation

Kim et al (2007, 2008) introduced optimal interpolation (OI) of HF radar (HFR) data. Here we examine the limitations of the OI method used to process the HFR data. We then identify major surface current patterns using results from OI. HFR data from 2010 are shown in Fig. 1, estimated by least-squares (LS) and OI methods. Spurious current vectors seen in the LS estimate (blue circles) are removed in the OI estimate. Moreover, OI provides larger data coverage.





Fig.4. Locations of gridpoints for gap sensitivity experiment.

The results show that gridpoints with high AR and low ROR (e.g., IS, IN) are resilient to gaps. Skills for gridpoints near the boundary of the radar mask (e.g., ENW, CN, ENE1, ENE2,) drop significantly if gaps in the searching radius increase. The corresponding condition numbers of the weighting matrices become more variable, making OI estimates unstable and less accurate.

Fig.1. Comparison between (a) LS and (b) OI estimates.

Error analysis

We compute an analytical surface current field of two eddies propagating southward in the northeastern Chukchi Sea. This flow field is then projected onto a radial grid pattern originating from each radar field site. The resulting velocities are used to estimate current vectors using OI. This approach helps us evaluate the limitations of OI by comparing the OI estimates with the known analytical field. This assessment is conducted by computing the skill score on a 0 - 1 scale (Warner et al., 2005) and the resulting phase shift (Shay et al., 2007) (Fig.2).





Fig.5. Variation in OI estimate skill (solid lines) and the condition numbers of the weighting matrices (dashed line) under different gap percentages in the searching radius.

Major surface current patterns

Based on these results we next apply the Self-Organizing Map (SOM) method (Mihanović et al., 2011) to HFR and wind velocities and identify six circulation patterns. The data set comprises of daily averaged regional NARR (red) and Barrow Airport (black) winds, as well as daily averaged surface current vectors (blue) with OI skill larger than 0.8 from 2010-Sep-12 to 2010-Oct-27 (Fig.6a). SOM patterns result in northeastward (NE) flow when winds are weak or from the east, with flow reversal (SW flow) occurring when NE wind speeds are larger than 10 m/s. Flow is transitioning during wind relaxation (Fig. 6b).

Fig.2. (a) Spatial distribution of skill of OI estimates and (b) resulting phase shift. Black dots indicate locations of permanent raw data gaps. The spatial distributions of skill and phase shift are controlled by: 1) available number of radials (e.g., velocity measurements) (AR) in the searching radius (35 km), 2) ratio of overlapping radials (ROR) in the searching radius and 3) condition number (CN) of the weighting matrix (Fig.3).







red: NE flow black: transition blue: SW flow 09/12 09/19 09/26 10/03 10/10 10/17 10/24 Fig.6. (a) Patterns of surface currents (blue) and corresponding winds (red/black). Best-Match-Units (BMU) and frequency of occurrence are shown in blue text. (b) Time series of corresponding BMU.