surface feature (top right of Panel a). The T–S cross-covariance has equally dynamically evolved towards more complex shapes (bottom left of Panels a-b), and has now weak connections with Ionian slope processes. Comparing the T-$\hat{u}$ (bottom right of Panels a–b) and T–$\hat{v}$ (top left of Panel b) with their initial values (Fig. 16), in the surface, they are tighter across and more elongated along the AIS meander (Fig. 12), and, on level 10, they are wider and longer. Finally, the T-ψ cross-covariance (top left of Panel a) has larger and rounder scales than initially, with a signature both within the Strait basin and Ionian slope region. Other such fields (Lermusiaux, 1997) show depth, region and process dependent horizontal scales. Near coastlines, the tracer auto-covariances are often close to coast-truncated ''Mexican hats''. Along the Ionian slope, the momentum (cross)-covariances usually consist of decaying wave patterns. Similar statements can be made for the vertical scales.

In conclusion, the error covariance has evolved according to the dominant nonlinear variations of the variability, with scales and processes a function of the region and depth considered. It is challenging to incorporate such complexities in the OI scheme. Setting the assimilation aside, ESSE can track and organize the nonlinearly evolving predictability/variations of variability subspaces. Further studies of such subspaces and dominant covariances, with perhaps subsequent analysis using mathematical tools tailored to the phenomena of interest (e.g., energy and vorticity analysis via ESSE), should be very helpful in understanding complex multivariate geophysical systems.

3.2.1.3. Dominant error covariances after assimilation and error learning. The a posteriori 3D multivariate RMS error fields corresponding to the analysis plotted on Fig. 12d have been exemplified by the real-time map of Fig. 1c. As one would expect from uniform mesoscale error weights, the error is reduced around the location of the data. However, the peculiarities of the dynamics affect this simple result (Lermusiaux, 1997). Briefly, the error is for example reduced along the advection path of the meandering AIS, all across the Channel. East of the missing data region at (35.6°N, 16.4°E) (Fig. 4b), the error reduction has tighter zonal scales than elsewhere, in accord with the local predictability error patterns portrayed on Fig. 14 (AIS bifurcations or filaments along the slope, etc). In practice, such a posteriori error fields are useful to design future sampling strategies (Section 1). Their 3D multivariate values (not shown) indicate that to best reduce uncertainties on Sept. 18, one should investigate the MCC, SMV and deep Ionian slope regions, with both hydrographic and velocity sensors.

Fig. 18 illustrates the adaptive component of the present estimation methodology: the dominant error covariance matrix is learning (e.g., Brockett, 1990) from the possibly significant data residuals. The procedure is detailed in Section A.3. On Sept. 18, the a posteriori residuals are first objectively analyzed. Their surface values are shown on Panels a–b. The amplitudes of the gridded T residuals are below the T measurement error, but those of the S residuals are at some locations larger than the S measurement error. This could be due to the approximate salinity data estimate (Section 2.3) or to the neglected model errors. The significant residuals are then combined with the a posteriori error subspace, leading to an ''adapted'' error subspace estimate (Section A.3, Eqs. (A22) and (A23)). Presently, their effect distinctly shows up within the adapted error eigenvectors 80 to 90; the surface salinity of the adapted vector 81 is given on Panel (c)