Reduced-order models (ROMs) of parametric systems traditionally operate by constructing a (local) parametrically-constant basis in an offline training phase. In the online phase, a ROM leveraging this basis is executed for each new parameter instance. These ROMs can be expensive as they (1) don't reduce the parametric dimension of the problem and (2) are Kolmogorov n-width limited for certain classes of problems, e.g., advection dominated systems. In this work, we employ deep learning to learn parametric-space-time trial subspaces. Bases associated with these subspaces are then used to construct a global parametric-space-time ROM, a single solve of which yields the solution for the entire parametric-space-time domain. Numerical experiments on benchmark problems from fluid dynamics characterized by a slowly decaying Kolmogorov n-width demonstrate that the approach is capable of outperforming existing model reduction approaches at a significantly reduced online cost.