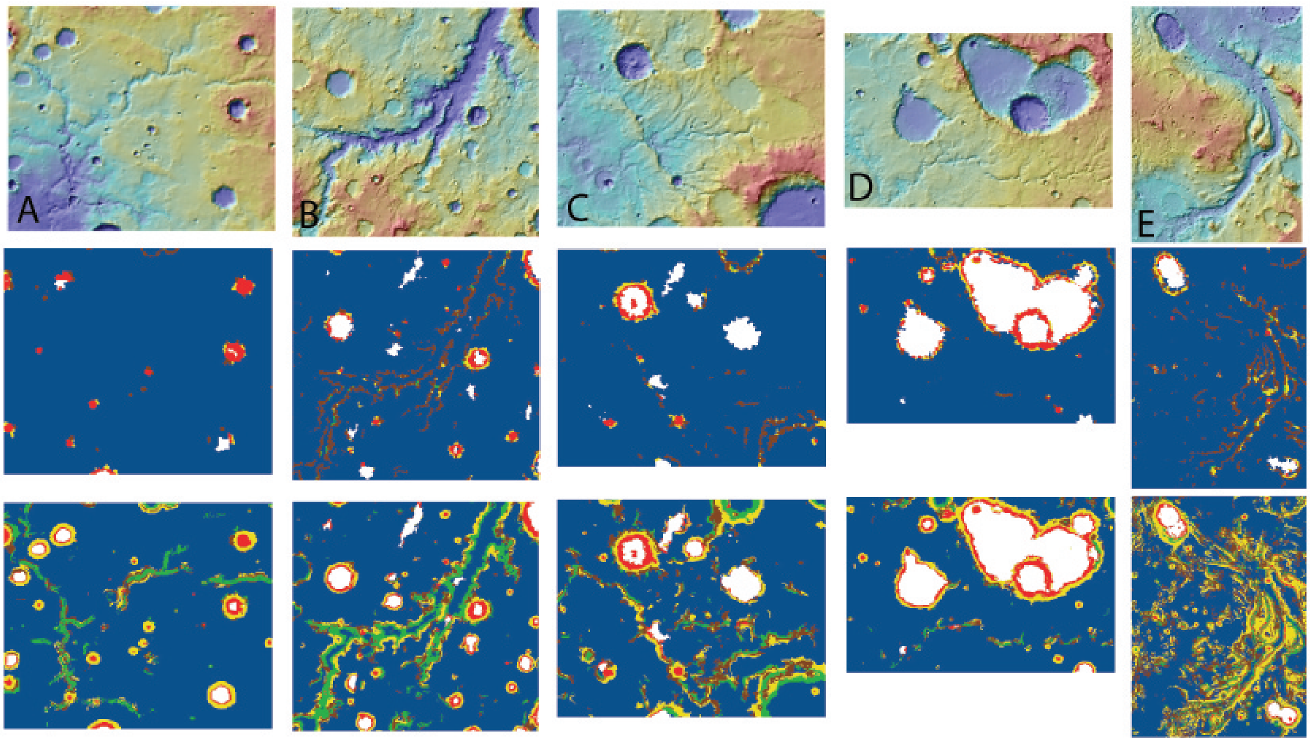

Fig. 5. Automatically generated six-landform geomorphic maps of Vichada (A), Al-Qahira (B), Dawes (C), Evros (D), and Margaritifer (E) sites using the SVM classifier. The top row shows sites' topography, the middle row shows maps originating from the watershed segmentation, and the bottom row shows the maps originating from the K-means segmentation. For the map legend see Fig. 4.

TABLE V
ACCURACY OF MAPPING INDIVIDUAL LANDFORMS IN THE VICHADA SITE USING DIFFERENT CLASSIFIERS. THE ENTRIES FOR LANDFORMS ARE (PRECISION / RECALL). **NB** – NAIVE BAYES, **B** – BAGGING WITH C4.5, **SVM** – SUPPORT VECTOR MACHINES.

watershed based segmentation							
classifier	**overall accuracy**	**plateau**	**floor**	**cvx. wall**	**con. wall**	**cvx. ridge**	**con ridge**
NB	83.05	0.86 / 0.99	0.40 / 0.30	0.73 / 0.21	0.41 / 0.06	0.001 / 0.0003	0.025 / 0.007
B	85.03	0.87 / 0.99	0.49 / 0.25	0.66 / 0.60	0.60 / 0.31	0.35 / 0.03	0.07 / 0.003
SVM	83.79	0.85 / 0.99	0.44 / 0.23	0.66 / 0.37	0.87 / 0.07	0.0 / 0.0	0.02 / 0.002
K-means based segmentation							
classifier	**overall accuracy**	**plateau**	**floor**	**cvx. wall**	**con. wall**	**cvx. ridge**	**con ridge**
NB	39.60	0.97 / 0.36	0.0 / 0.0	0.62 / 0.73	0.31 / 0.09	0.81 / 0.11	0.67 / 0.25
B	69.20	0.94 / 0.75	0.71 / 0.78	0.54 / 0.69	0.73 / 0.46	0.10 / 0.84	0.09 / 0.008
SVM	86.00	0.92 / 0.95	0.60 / 0.82	0.80 / 0.44	0.60 / 0.66	0.41 / 0.56	0.25 / 0.08

labels (i.e., for machine generation of geomorphic maps). This is a challenging problem for the following reasons. First, landscapes are more difficult to label than multi-spectral images because their characterization is based on fewer features. A multi-spectral image has at least six channels (colors), whereas landform characterization tends to be limited (our study derives three topographic features). Second, space-related data exhibits less quality than terrestrial data. A Martian DEM is much coarser and noisier than terrestrial DEMs. High quality DEMs facilitate extraction of additional features (such as several types of surface curvature). Moreover, terrestrial topographic data can often be supplemented by other datasets, such as, for example, hydrological data. Such additional datasets are not available in space applications. Developing an application for mapping planetary surfaces, therefore, presents challenges not found in the terrestrial domain. Our approach is based on a segmentation step preceding classification; this is because segments offer the opportunity to create additional features, taking into account spatial context (albeit only local context). This work is intended to serve as a guideline for future work related to automated planetary mapping. It is important to add that the particular landform classes presented in this paper are examples of geomorphic studies of cratered terrain on planet Mars. In order to apply our framework to generate maps of different landforms of interest on Mars, Earth or other planets, different classes must be identified by a domain expert (resulting in different training sets).

As a result of our assessment of different segmentation and classification algorithms, we offer the following design choices for future machine mapping applications. For a rough map