Deep visual models achieve strong performance when the training and test data are drawn from similar distributions. However, their reliability often deteriorates under real-world distribution shifts caused by adverse weather, changing illumination, background variations, and sensor noise. This work presents research aimed at improving the robustness and adaptability of visual models under such distribution shifts, with a particular focus on all-weather semantic segmentation and domain-generalized visual regression. The first part of the work focuses on urban-scene semantic segmentation under challenging conditions, including fog, rain, snow, and nighttime environments. It presents test-time and continual adaptation methods that improve pretrained models without requiring labeled target-domain data. These methods leverage edge consistency, domain-aware self-distillation, and boundary-guided prompt learning. This work also examines the efficient adaptation of vision foundation models by updating only a small number of parameters while keeping most of the backbone frozen. The second part addresses domain generalization for visual regression, where models may rely on label-irrelevant visual factors and consequently fail to generalize to unseen domains. A framework is presented that disentangles task-relevant representations from latent distractors and enforces prediction consistency under photometric perturbations. Collectively, this research contributes methods for developing visual models that are more robust, adaptable, and reliable under real-world distribution shifts.