Mid-latitude cyclones produce wind storms across much of Europe predominantly during the winter months and are responsible for most of the insured losses due to destructive natural hazards in the region (Pinto et al. 2010). Much of the infrastructure-related destruction is attributable to extreme wind speeds that often impact multiple countries (Leckebusch et al. 2007, Pinto et al. 2010). In central Europe alone, 56 percent of economic and 64 percent of insurance losses caused by natural hazards are due to these winter storms (Hofherr and Kunz 2010). The Lothar storm (25-27 December 1999) is considered one of the most expensive storms in European history for insurance companies (Wernli et al. 2002, Leckebusch et al. 2007). Other similarly dangerous recent storms include Kyrill (16-19 January 2007), Jeanette (26-28 October 2002), and Emma (29 February – 2 March 2008) (Heneka and Hofherr 2011). Wind station data must be analyzed accurately and appropriately to determine wind speed-damage relationships associated with these storms.

Some limitations complicate the use of station data to represent a wind field across a single storm. Klawa and Ulbrich (2003) stated that a single station can represent a local climate that is very different from the regional climate, highlighting the uncertainty that microclimatology may present when examining macroclimatological patterns. Hofherr and Kunz (2010) emphasized the importance of high spatial resolution of station data to estimate wind storm climatology accurately and to evaluate how local topographic features influence the wind field. At the local scale, orographic influences, land use, friction, and boundary layer processes modify both the strength and direction of the synoptically-generated surface winds. Gusts are most dependent on the roughness length of the terrain. Because of these local factors, the wind climatology of a station may depart considerably from those expected from the macroscale climatology (Hofherr and Kunz 2010).

Considering both micro- and macroclimatic patterns, there are many ways to simulate and interpolate wind surfaces. Kriging interpolation methods are the most common stochastic techniques; these apply probability and spatial correlation to create a surface that is weighted by observed values through a semi-variance function. Distance and direction are both utilized for the semi-variance function so it can account for anisotropic spatial patterns and trends in wind behavior (Luo et al. 2008). Since wind speeds often exhibit a direction in which they are increasing or decreasing across a surface, kriging methods are preferred over deterministic methods and other stochastic methods (Lanza et al. 2001, Luo et al. 2008, Akkala et al. 2010, Zlatev et al. 2010).

In a recent study by Luo et al. (2008), various forms of kriging interpolated surface winds more accurately than other methods based on their mean error (ME) and root mean square error (RMSE). Luo et al. (2008) concluded that kriging and co-kriging were best, with co-kriging performing slightly better. The widely-varying terrain of Austria presents a challenge to the ordinary kriging approach, thus presenting an ideal case study for applying a co-kriging technique utilizing multiple covariates that will include elevation, aspect, and landcover.