PROGRESS ON PREDICTING CROP YIELD LOSS FROM WEEDS

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Increasing concerns about the environmental impacts of herbicides, the development of herbicide-resistant weeds, and the need to carefully weigh costs and benefits have led to greater interest in developing rational, economical, and sustainable approaches to weed management (O'Donovan 1996). In addition, greater emphasis on post-emergence applied herbicides such as glyphosate has allowed for more flexibility in herbicide application timing, but more information is often required to effectively time applications to maximize efficacy (Boerboom, 2002; Kropff and Walter, 2000). A continuum of approaches exists for making weed management decisions, ranging from informed but subjective assessments made by farmers to recommendations produced by computerized decision-support tools, such as WeedSOFT (Mortensen et al., 1999). An optimal weed management approach will not simply maximize weed control but will also maximize economic gains while minimizing environmental risks. Since several outcomes must be considered simultaneously, and because interactions among numerous variables contribute to each outcome, the task of deciding upon an optimal weed management approach is complex and thus the role of comprehensive decision support tools has become more important. Furthermore, previous research has indicated that recommendations generated by decision support tools are often superior to subjective assessments in reducing weed populations and maximizing gross income (Wilkerson et al., 1991).

Most current weed management decision support systems integrate biological and economic data to generate herbicide application recommendations aimed at maximizing benefits while minimizing costs and risks. Information inputs can include crop and weed growth stages, weed species and densities, crop type and spacing, crop rotation, soil type, average precipitation, critical periods for weed control, weed economic thresholds, weed seed production, herbicide efficacy, herbicide application restrictions, and economic costs of herbicide applications including technology costs (O'Donovan, 1996). Predictions of crop yield loss resulting from weeds are a critical component in determining both critical periods of weed control and weed economic thresholds (Swanton and Murphy, 1996). Unfortunately, no simple empirical approach adequately predicts yield loss from weeds because yield loss per unit of weed varies greatly with emergence timing, relative weed-crop size, species composition of the weed community, and many edaphic and environmental factors. Therefore, a greater understanding of how these many variables influence crop-weed interference may aid in the development of better approaches to predict yield loss from weeds.

Potential crop yield loss resulting from a given weed population has been predicted using several approaches. The simplest approach involves relating yield loss empirically to weed density. When yield loss is plotted as a function of weed density, yield loss typically increases linearly with increased weed density at low to moderate densities and reaches an asymptotic maximum at high weed densities. This type of sigmoidal curve is usually described mathematically as an exponential or hyperbolic function (Cousens, 1992). Numerous experiments relating crop yield losses to weed density alone have shown that this type of model can adequately describe a specific dataset, but such strictly empirical models are not robust temporally or spatially and therefore lack broad applicability. Hyperbolic models of density-

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dependent yield loss can be improved by the addition of modifying coefficients that quantify the relative size of weeds and crop and the relative competitiveness of different weeds species. This approach is used by WeedSOFT to determine crop yield loss. But one difficulty of this approach is that the modifiers of weed competitive ability change among different regions and are largely based on subjective opinions of various experts. Consequently, the competitive indexes for each weed species must be determined independently for each region. Other variations of this empirical crop yield model substitute relative leaf area (RLA) (Kropff et al., 1992) or relative shoot volume (RSV) (Bussler et al., 1995) for density. These modifications were proposed as a means to account for both density and differences in growth stage caused by differential emergence timing. However, a series of weed-crop competition experiments conducted at UW-Madison demonstrated that variability in crop yield loss was not adequately explained by variations in weed density, RLA, and RSV (Conley et al., 2003; Moechnig et al., 2003).

Because of the limitations of empirically derived models of crop yield loss, the attention of some researchers has shifted towards understanding the mechanisms of crop-weed interference that are the underlying causes of yield loss (Swanton et al., 1999). It is hoped that such an understanding will aid in the development of more robust models used to predict crop yield loss from weeds. Interference between individual plants occurs when the presence of one plant has an influence on the growth and development of another plant. Interference is a general term for any kind of interaction, whether the outcome is positive, negative, or neutral for one or both of the interacting individuals. Competition is a more specific term for a mutually adverse interaction between two individual plants. When two plants are in close proximity to each other resources such as water, light, and nutrients may become insufficient for optimum growth of each plant (Radosevich et al., 1997). If one plant is able to acquire resources more efficiently than another, or if one plant can better tolerate the resource reduction, then that individual plant will have a competitive advantage over the other (Tilman, 1997).

Competitive interactions are the primary drivers of crop yield losses from weeds, since the presence of weeds can deprive crop plants of adequate resources needed for growth. But other kinds of interactions may be important in influencing the effect that one plant may have on a neighboring plant (Radosevich et al., 1997). For instance, if a plant such as giant foxtail obtains structural support from a nearby corn plant by leaning against it, it may be able to allocate more biomass to leaf rather than stem production (Moechnig, 2003). In this instance, the corn plant may have both positive and negative effects on the growth of the giant foxtail plant. Some types of interactions are thought to occur between two neighboring plants before they begin to compete for limited resources. For example, one plant alters the quality, or spectral composition, of the light environment around a nearby plant such that red wavelengths are reduced while far-red wavelengths are not affected. Plants can sense these subtle changes in light quality and respond by altering growth patterns in ways that favor future competitive success. Documented responses to changes in light quality include decreased lateral branching, increased stem elongation, and reduced root/shoot ratios (Ballaré and Casal, 2000).

Recent research conducted at UW-Madison has focused on characterizing crop-weed interactions using simple models that incorporate mechanistically based parameters to describe plant growth. Moechnig (2003) developed a growth model of giant foxtail, common lambs-quarters, and corn in mixed communities based on data collected from these species grown in monoculture. The model accurately predicted shoot height and biomass across several plant densities or competitive environments. Plant height was predicted as a function of wind stress whereas biomass accumulation was predicted as a function of light use-efficiency (LUE) (Moechnig, 2003). Gramig et al. (2002) determined values of LUE for six additional weed species grown in monoculture or in corn to characterize the effect of different competitive environments on potential weed biomass accumulation. Results indicated that weed species LUE values were greater in more competitive corn-weed communities (Gramig et al., 2002). A function was developed that adjusted LUE values with variation in weed density and canopy structure and which was used to predict weed LUE in monoculture and in corn. The function accurately predicted LUE values for weeds in monoculture but slightly underestimated the LUE values for weeds grown in corn (Gramig, 2003, unpublished data). These research efforts provide evidence that a simplified mechanistic approach to characterize crop-weed interactions may be feasible, but many challenges remain. Future research is planned to continue working on mechanistic characterization of weed-crop communities, focusing mainly on light interactions, and also to explore the potential effects of early-season shifts in light quality on competitive interactions between weed and crop plants.

References

Ballaré, C.L., and J.J. Casal. 2000. Light signals perceived by crop and weed plants. Field Crops Res. 67:149-160.

Boerboom, C. 2002. Time of weed emergence and economic impact on crops. Proc. Wisc. Fert. Aglime and Pest Management Conf., Coop. Ext. Ser. Univ. Wisc.-Ext. and Coll. Agric. Life Sci., Univ. Wisc.-Madison. 41:209-213.

Bussler, B.H., B.D. Maxwell, and K. J. Puettman. 1995. Using plant volume to quantify interference in corn (*Zea mays*) neighborhoods. Weed Sci. 43:586-594.

Conley, S.P., D.E. Stoltenberg, C.M. Boerboom, and L.K. Binning. 2003. Predicting soybean yield loss in giant foxtail (*Setaria faberi*) and common lambsquarters (*Chenopodium album*) communities. Weed Sci. 51:402-407.

Cousens, R.D. 1992. Weed competition and interference in cropping systems. Proc. First International Weed Cont. Cong., University of Sydney, Melbourne. pp. 113-117.

Gramig, G.G., D.E. Stoltenberg, and J.M. Norman. 2002. Stability of radiation-use efficiency for estimating weed biomass accumulation in weed-corn communities. North Central Weed Sci. Soc. Abstr. 57:57. [CD-ROM Computer File]. North Central Weed Sci. Soc., Champaign, IL (Dec. 2002).

Kropff, M.J., and H. Walter. 2000. EWRS and the challenges for weed research at the start of a new millennium. Weed Res. 40:7-10.

Kropff, M.J., S.E. Weaver, and M.A. Smits. 1992. The use of ecophysiological models for crop-weed interference, relative leaf area, and yield loss. Weed Sci. 40:296-301.

Moechnig, M.J. 2003. A mechanistic approach to predict weed-corn growth interactions. PhD. Dissertation, University of Wisconsin, Madison.184 pp.

Moechnig, M.J., D.E. Stoltenberg, C.M. Boerboom, and L.K. Binning. 2003. Empirical corn yield loss estimation from common lambsquarters (*Chenopodium album*) and giant foxtail (*Setaria faberi*) in mixed communities. Weed Sci. 51:386-393.

Mortensen, D.A., A.R. Martin, F.W. Roeth, T.E. Harvill, R.W. Klein, M. Milner, G.A. Wicks, R.G. Wilson, D.L. Holshouser, D.J. Lyon, P.J. Shea, and J.T. Rawlingson. 1999. WeedSOFT Version 4.0 User's Manual. University of Nebraska, Lincoln. 22 pp.

O'Donovan, J.T. 1996. Computerized decision support systems: Aids to rational and sustainable weed management. Can. J. Plant Sci. 76:3-7.

Radosevich, S., J. Holt, and C. Ghersa. 1997. Associations of weeds and crops. pp. 162-217 *In* Weed Ecology. John Wiley & Sons, Inc., New York.

Swanton, C.J., and S.D. Murphy. 1996. Weed science beyond the weeds: the role of integrated weed management in agroecosystem health. Weed Sci. 44:437-445.

Swanton, C.J., S. Weaver, P. Cowan, R.V. Acker, W. Deen, and A. Shreshta. 1999. Weed Thresholds: Theory and Applicability. pp. 9-29 *In* D.D. Buhler (ed.) Expanding the Context of Weed Management. Food Products Press, New York.

Tilman, D. 1997. Mechanisms of plant competition. pp. 239-261 *In* M.J. Crawley (ed.) Plant Ecology. Blackwell Science, Oxford, London.

Wilkerson, G.G., S.A. Modena, and H.D. Coble. 1991. HERB: Decision model for postemergence weed control in soybean. Agron. J. 83:413-417.